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Development of A Novel Discharge Routing Method Based On the Large Discharge Dataset, Muskingum Model, Optimization Methods, and Multi-Criteria Decision Making

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ABSTRACT

Discharge routing is a key method for predicting downstream hydrograph in canals or rivers. Predicting the downstream hydrograph using the upstream hydrograph can significantly decrease the flood damages. A combination of a large dataset and Muskingum model can enhance river discharge routing reliability. However, calibrating the Muskingum model for large datasets requires powerful optimization algorithms. Metaheuristic Optimization Algorithms (MOAs) can accurately calibrate the Muskingum model, but their performance may vary. Hence, in the present study, a new technique is introduced for discharge routing based on the large discharge dataset: Muskingum model, MOAs, and Multi-criteria Decision-Making (MCDM). Different MOAs, including a Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Firefly Algorithm (FFA), Cuckoo Search (CS), Bat Algorithm (BA), Shark Smell Optimization (SSO), Whale Optimization Algorithm (WOA), Harris Hawk's Optimization (HHO), and hybrid of WOA and CS (WOA_CS), were developed for Muskingum calibration. The Mollasani-Ahvaz, Harmaleh-Bamdej river reaches Karun basin, and Lighvan-Heravi in the Urmia basin are considered case studies. Results of discharge routing based on the evaluation criteria in the training period showed MOAs were trained with high accuracy and reliability. While in the testing period, each MOA achieves better results in some evaluation criteria. Considering all evaluation criteria using the MCDM showed that WOA_CS, WOA, and FFA were placed in the first, second, and third rankings, respectively. The MCDM scores for WOA_CS, WOA, and FFA were equal to 0.960, 0.913, and 0.907, respectively. The developed method in this study has a good potential for discharge routing in various river reaches.

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1. Introduction

Flood is one of the most important natural hazards that has caused humans to manage damages to manufactured structures, human life, and countries' economies. Management of this phenomenon has always been a solution to control and reduce its damages. Discharge forecasting is an essential tool for managing it. In this regard, discharge and flood routing are two of the best management methods. There are two crucial discharge or flood routing techniques: hydraulically and hydrologically. Hydraulic methods have a complex structure and need many input parameters, such as geometry and riverine characteristics. In contrast, hydrological methods have a simple structure and are only executed by a few parameters. The Muskingum model is one of the most famous hydrological discharge or flood routings researchers widely use because of its simplicity and fewer computation times than similar methods [1,2].

So far, different Muskingum models have been introduced for the discharge or flood routings. In following some of well-known Muskingum models are reviewed. Gavilan and Houck [3] introduced two Muskingum models for flood routing. These models used three parameters and were a linear relationship between storage and weighted inflow and outflow. Gill [4] reported that there is much error if the relationship between storage and flow is linear. Therefore, Gill modified the linear Muskingum model as a nonlinearity. This model was similar to the proposed relationship with Gill [4], but it has a power parameter for inflow and outflow. The fourth Muskingum model had four parameters and was presented by Easa [5]. This model is the weighted sum of inflow and outflow in power form. In the fifth relationship, Haddad et al. [6] defined seven parameters for the Muskingum equation. This model was more accurate than other previously established Muskingum models. Zhang et al. [7] proposed a Muskingum model for considering lateral flow. The mentioned Muskingum models require parameter determination prior to execution. There are three methods to find the best parameters for the Muskingum model: graphical, moment and cumulants, and optimization algorithms. The mentioned methods work for earlier versions of Muskingum models, but they don't apply to models with over three parameters. Therefore, using optimization algorithms is necessary to find the best parameters for new Muskingum models. Although some optimization algorithms estimate the Muskingum model's parameters with good accuracy, however, mathematical and numeric optimization algorithms have the limitation in solving Muskingum models with numerous parameters and constraints. Mathematical optimization algorithms only solve differentiable objective functions. As the number of decision variables and constraints increases, the computational efforts of numeric optimization algorithms grow exponentially. However, metaheuristic optimization algorithms (MOAs) can efficiently solve any optimization problem. In solving a wide range of optimization problems, MOAs are faster and require less computation cost than mathematical or numeric optimization methods [8]. Hence, in recent years, MOAs have successfully solved flood discharge routing problems. Farzin et al. [9] used an improved bat algorithm (IBA) and the three-parameter Muskingum model in different Wilson, Karahan, and Myanmar River flood case studies. Results showed more accuracy of IBA than bat algorithm (BA), particle swarm optimization (PSO), and genetic algorithm (GA). In Wilson, Karahan, as well as Viessman and Lewis case studies, Node Farahani et al. [9] Employed the kidney algorithm (KA) to find the

optimal parameter of the four-parameter Muskingum model for flood routing. Their results indicated better results for KA compared with GA and PSO. Also, this study reported that the four-parameter Muskingum model outperforms the three-parameter Muskingum. Farahani et al. [10] applied the shark algorithm (SA) to optimize the four-parameter Muskingum in flood routing of three benchmark case studies, and the results showed that the SA is more capable than various optimizers such as the harmony search (HS) algorithm. Akbari et al. [11] employed the hybrid of PSO and GA to find the optimal parameters of the four-parameter Muskingum model in the four benchmark case studies. They indicated good application of this method compared to other metaheuristic algorithms such as KA. Norouzi and Bazargan [12] used linear Muskingum for four floods in the Karun River. In this study, the parameters of the Muskingum model were calibrated for all four floods, and the results demonstrated improved food routing accuracy using an investigated approach. Niazkar and Zakwan [13] applied the new four parameters Muskingum method to solve Wilson, Viessman and Lewis, and Wye floods. This study employs the modified honey bee Mating Optimization, the Generalized Reduced Gradient, and the hybrid. Results indicate the better accuracy of the hybrid algorithm. Moradi et al. [14] introduced the Muskingum model with twelve parameters. In this model, the lateral flow was considered and the parameters of the model were obtained with the gorilla troop optimizer.

In the most previously conducted studies, only floods with one peak or a few peaks were used for flood routing. The calibration period in the mentioned studies needed to be longer compared to the actual conditions. The Muskingum model may only accurately predict downstream discharge data in different conditions if calibrated with more than one flood event. This issue can be addressed by discharge routing. In discharge routing, the downstream river's discharge is predicted based on the upstream river's discharge. In the discharge data with long periods, there are many floods and drought events. Therefore, predicting discharge data can help water resource management with high reliability. To address this issue, some studies have been performed by researchers. Perumal and price [15] introduced variable parameters McCarthy–Muskingum model, one physically based variable parameter Muskingum method developed from the full Saint–Venant equations. This method was used in different studies, such as Yadav et al. [16], Barbetta et al. [17], and Yadav et al. [18], for discharge routing in various case studies. However, this method has drawbacks, such as needing initial and boundary conditions and needing too much physical data for execution. Integrating the Muskingum model with optimization algorithms can address discharge routing with a large discharge dataset. Recently, new metaheuristic algorithms such as grey wolf optimizer (GWO) [19], whale optimization algorithm (WOA) [20], grasshopper optimization algorithm (GOA) [21], modified ideal gas molecular movement algorithm [22], Harris hawk's optimization (HHO) [23], hybrid generalized reduced gradient-based particle swarm optimizer [24], gradient-based optimizer (GBO) [25], improved chaotic ideal gas molecular movement [26], hybrid grey wolf optimizer (GWO) combined with elephant herding optimization (EHO) [27], and opposition-based ideal gas molecular movement algorithm [28], because of their high ability in finding optimal solution gained more attention of researchers. These algorithms have successfully been applied to engineering problems such as predicting soil electrical conductivity [29], optimal design of water distribution networks [30],

tuning machine learning methods [25−27], water resources demand forecasting [34], optimization of hydrothermal scheduling [35] as well as open channel designing [36].

The other topic of debate for scientific society is selecting the best algorithm for optimization engineering problems. Because there are many criteria for choosing the best optimization algorithm, such as accuracy and time computing in finding the optimal solution, multi-criteria decision-making (MCDM) can be one ideal solution to choosing the best algorithms by considering all the mentioned criteria. Researchers widely used the MCDM methods to select the best optimization algorithm in assessing the relationships between the water control infrastructure and water governance [37], optimal operation of benchmark reservoirs [38] for choosing the best machine learning [39,40], and hydrochemical assessment of groundwater suitability for irrigation [41].

According to the best author's knowledge, the lack of using a large discharge dataset, discharge routing with efficient methods, integrating the new Muskingum model with powerful MOAs, and selecting the best MOAs for optimizing the Muskingum model are the main gaps in previous research. Hence, this study aims to address these gaps using developing one new approach to discharge routing. In this approach, the integration of the Muskingum model and different MOAs are developed for discharge routing. In this approach, a large discharge river flow dataset is employed for training and testing the Muskingum Model. Moreover, the MCDM is used to select the best MOAs in the performance optimization of the Muskingum model. This approach can apply to other case studies for discharge routing.

2. Research significance

Integrating MOA, the Muskingum method, and MCDM can increase the accuracy and efficiency of large-scale discharge routing. This approach unlike other discharge simulation methods only needs to upstream hydrograph of river discharge and can be used in water resources management and flood warning systems. Some studies used the Muskingum method for flood routing; however, they only consider large-scale river discharge, leading to unreliable models and underestimating results. Some studies used physical methods such as variable parameter McCarthy–Muskingum for large-scale river discharge. However, this method needs many datasets, such as lateral flow, physical and geometric characteristics of rivers, and high-time computing for solving physical equations in the problem domain. Hence, the present research has focused on developing a new technique by integrating MOAs, the Muskingum method, and MCDM. Moreover, in the present study, long-term daily runoff data containing many flood events will calibrate a seven-parameter Muskingum model. The presented method can provide more reliable results by considering the entire river flow (base flow + flood wave) in a long statistical period. Unlike in previous studies, part of the data will be used to validate the obtained model. It is worth mentioning that three different case studies, including the Mollasani-Ahvaz, Harmaleh-Bamdej river reaches in the Karun basin, and Lighvan-Heravi in the Urmia basin in Iran, are chosen to investigate the application of MOAs in optimizing the Muskingum model. The results of MOAs are also compared, and the best algorithm is selected by employing

MCDM. Finally, the best parameters of the Muskingum model and their outcomes for flood routing are reported. Figure 1 shows the flowchart of the present study.

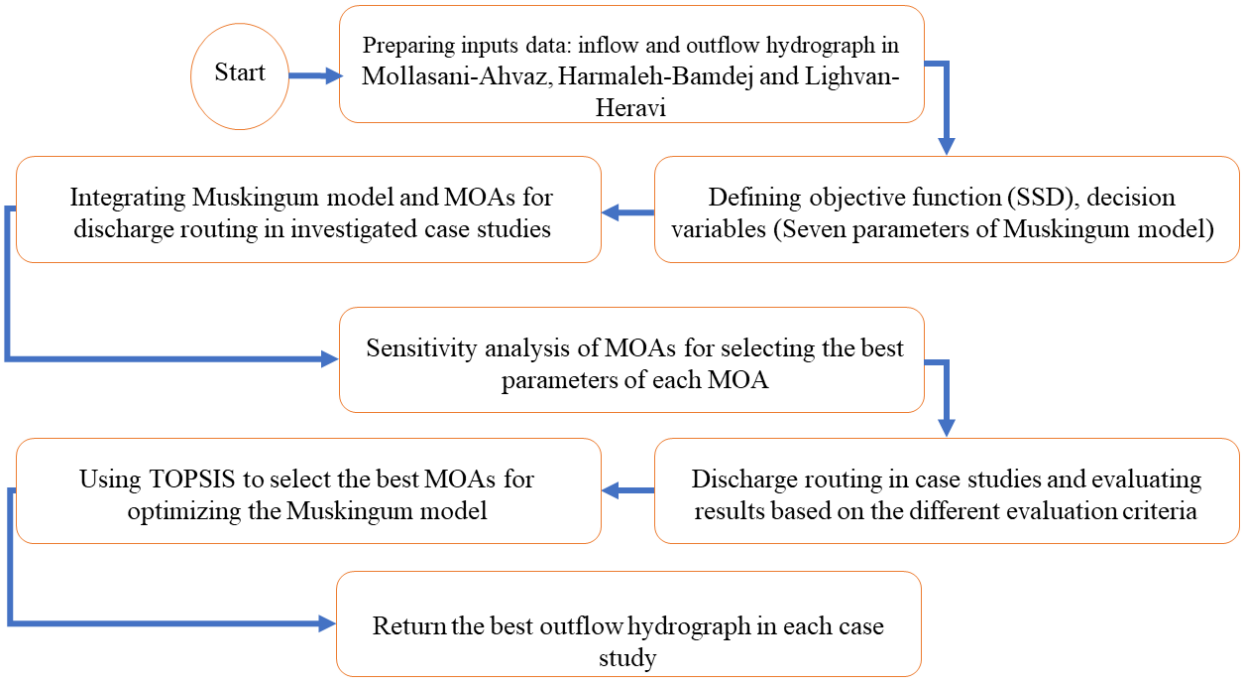

Start
Preparing inputs data: inflow and outflow hydrograph in Mollasani-Ahvaz, Harmaleh-Bamdej and Lighvan-Heravi
Defining objective function (SSD), decision variables (Seven parameters of Muskingum model)
Integrating Muskingum model and MOAs for discharge routing in investigated case studies
Sensitivity analysis of MOAs for selecting the best parameters of each MOA
Discharge routing in case studies and evaluating results based on the different evaluation criteria
Using TOPSIS to select the best MOAs for optimizing the Muskingum model
Return the best outflow hydrograph in each case study

Fig. 1. The flowchart of present study.

3. Methods

3.1. Case studies and data collection

The present study's three reaches are chosen as case studies, including Mollasani-Ahvaz and Harmaleh-Bamdej in the Karun basin and Lighvan-Heravi in the Urmia basin. The Mollasani-Ahvaz and Harmaleh-Bamdej reach the Karun basin and Karun River, one of Iran's perennial basin rivers. In addition, Lighvan-Heravi's reach is placed in mountainous regions of the Urmia basin, one of the most famous basins in Iran. Each of these reaches is placed in various morphological and climate conditions. Therefore, using these case studies can reveal the accuracy of the proposed method of discharge routing. Figure 2 shows the locations of the case studies in Iran. The inflow and outflow data of the mentioned reaches from 2011/03/21 to 2017/03/20 are used for the discharge routing. Table 1 shows the present study's usage data and its statistical criteria.

3.2. Muskingum model

The present study employs a new non-linear Muskingum model [7] with seven parameters, called the NL5 (mean fifth equation for non-linear storage-discharge relationship in natural stream), for the discharge routing. The NL5 considers the morphological changes between the upstream and downstream sections in a river reach, while other methods consider the same morphology characteristic along one river reach.

Table 1
Usage flow data and its statistical criteria.

Flow / Date	Mollasani (m^3/s)	Ahvaz (m^3/s)	Harmaleh (m^3/s)	Bamdej (m^3/s)	Lighvan (m^3/s)	Heravi (m^3/s)
2011-03-21	257	268.00	62.20	18.00	0.91	0.02
2011-03-22	241	263.00	58.10	17.60	0.96	0.02
2011-03-23	243	267.00	56.10	18.00	0.75	0.03
2011-03-24	243	268.00	54.80	17.60	0.70	0.03
2011-03-25	246	270.00	55.50	17.50	0.86	0.02
2011-03-26	249	271.00	54.80	17.50	0.91	0.20
2011-03-27	252	270.00	52.80	17.90	0.68	0.02
2011-03-28	243	245.00	53.50	18.70	0.46	0.02
2011-03-29	223	232.00	52.80	18.30	0.23	0.01
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
2017-03-11	386	374.00	105.00	5.88	0.16	0.011
2017-03-12	400	403.00	105.00	6.28	0.16	0
2017-03-13	378	351.00	105.00	6.49	0.16	0
2017-03-14	364	346.00	94.50	6.92	0.25	0
2017-03-15	366	345.00	94.50	6.81	0.30	0.015
2017-03-16	362	354.00	93.90	6.39	0.35	0.031
2017-03-17	368	370.00	93.90	6.28	0.30	0.046
2017-03-18	348	319.00	93.30	6.39	0.25	0.062
2017-03-19	326	315.00	99.80	6.7	0.25	0.077
2017-03-20	342	336.00	101.00	6.7	0.16	0.112
Statistical criteria						
Mean (m^3/s)	300.88	308.30	95.80	93.76	0.70	0.42
Max (m^3/s)	1357.00	1358.00	1360.00	1082.00	20.60	19.00
Min (m^3/s)	0.00	0.00	0.00	0.00	0.00	0.00
Std (m^3/s)	118.03	116.68	89.31	86.97	1.04	0.79

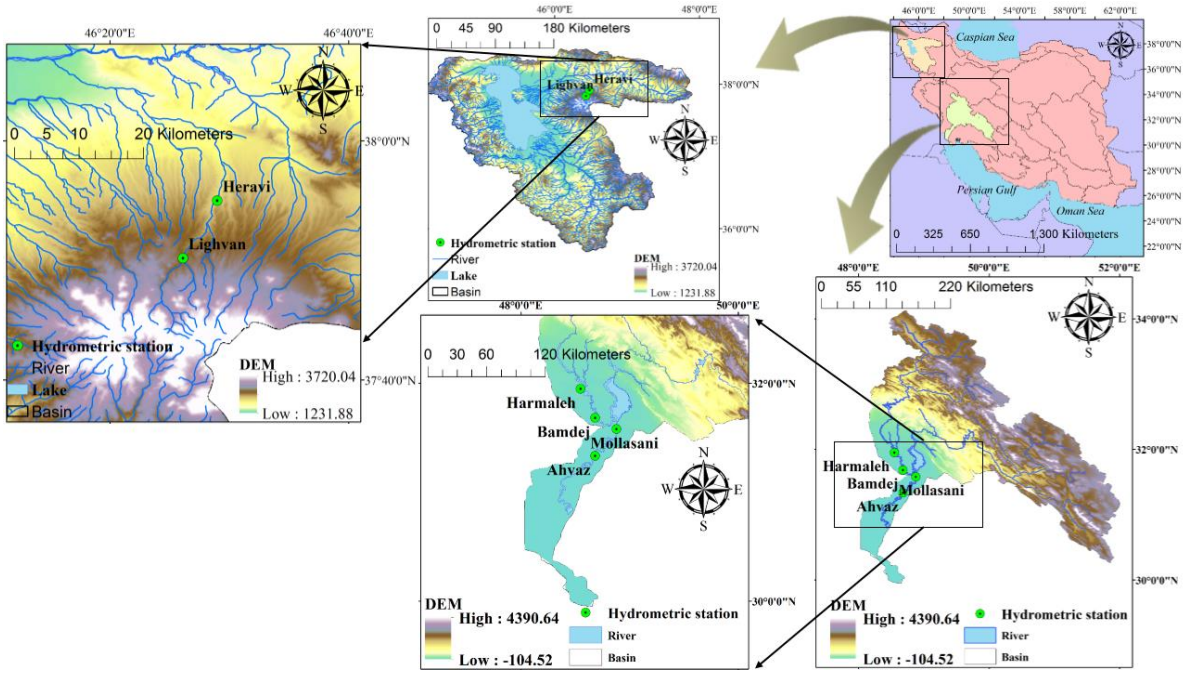


Fig. 2. The locations of the case study.

The main relationship in this method is expressed as follows:

$$S = K\left[X\left(C_1 I^{\alpha_1}\right) + \left(1 - X\right)\left(C_2 O^{\alpha_2}\right)\right]^{\beta} \quad (1)$$

In which, I is inflow, O is outflow, S is storage, K is time storage coefficient, X is a weighted factor that indicates the effect of inflow and outflow on storage, $C_1, C_2, \alpha_1$and α_2 are parameters for considering different morphology between the upstream and downstream sections, and β is one exponent.

3.3. Genetic algorithm (GA)

GA is an evolutionary optimization algorithm which had applications in different aspects, such as optimizing parameters of machine learning in streamflow forecasting [42]. In the GA first, we randomly generated the initial population. Then, the population evolves to achieve an optimal objective function in the optimization process. In this process, the selection operator selects a population of individuals with better objective functions. Afterward, the selected individuals are considered parent individuals. These parents produce children using the crossover and mutation operators. Each operator applies to parent individuals by a certain probability. The probability of crossover is called crossover probability, and the probability for mutation is called mutation probability. The relationship for the crossover operator is as follows:

$$Pop_i^{t+1} = \alpha * Pop_i^t + \left(1 - \alpha\right) Pop_j^t \quad (2)$$

$$Pop_j^{t+1} = \alpha * Pop_j^t + \left(1 - \alpha\right) Pop_i^t \quad (3)$$

In which, Pop_i^{t+1} is i^{th} children, Pop_i^t is i^{th} parent, Pop_j^{t+1} is j^{th} children, Pop_j^t is j^{th} parent, and α is a random number from 0 to 1. The mutation is defined based on the following relationship:

$$Pop_{i,j}^{t+1} = Lb_{i,j} + \beta * \left(Ub_{i,j} - Lb_{i,j}\right) \quad (4)$$

In which, $Pop_{i,j}^{t+1}$ denotes the i^{th} gene in j^{th} chromosome, $Ub_{i,j}$ is the upper bound of i^{th} gene in j^{th} chromosome, $Lb_{i,j}$ is the lower bound of i^{th} gene in j^{th} chromosome, β is a random number between 0 to 1. For more information, please see [43].

3.4. Particle swarm optimization (PSO)

PSO is a swarm-based algorithm which was employed in different fields, such as modelling streamflow [44]. The population in PSO is a group of particles. Each of these particles has one position, velocity, and an objective function. PSO updates the position and velocity of particles based on the best global experience of particles (X_{Gbest}) and the best personal experience of particles ($X_{Pbest,i}$). The best global experience of particles is an optimal solution for all particles found so far, and the best personal experience of particles is a better solution than each particle experiences. In PSO, the search process begins by generating a random initial population. Then the velocity and position of particles are updated based on the following relationship:

$$V_i^{t+1} = \omega * V_i^t + c_1 * rand * \left(X_{Gbest} - X_i^t\right) + c_2 * rand * \left(X_{Pbest,i} - X_i^t\right) \quad (5)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (6)$$

In which, V_i^{t+1} is the updated velocity of i^{th} particle, V_i^t is the old velocity of i^{th} particle, X_{Gbest} is the position of best global experience of all particles, $X_{Pbest,i}$ is the position of best personal experience of i^{th} particles, X_i^{t+1} is the updated position of i^{th} particle, X_i^t is the old position of i^{th} particle, ω is inertia weight, c_1 and c_2 are acceleration coefficients, and $rand$ is a random number between 0 and 1. For more information, please refer to [45].

3.5. Firefly algorithm (FFA)

FFA [46] inspires the firefly's attraction to the flashing light. FFA was used by [47] for streamflow forecasting. This algorithm works based on the three following concepts:

1. Each firefly is attracted to other fireflies, regardless of their sex.
2. The firefly's attractiveness is proportional to light intensity.
3. The objective function determines the light intensity of the firefly. In FFA, fireflies move toward fireflies with more light intensity (objective function). For more information about FFA, please see [48].

3.6. Cuckoo search (CS)

The reproduction strategy of cuckoo birds inspires CS [49]. In this strategy, the cuckoos' lay eggs in the other birds' nests. CS is developed based on the following assumptions:

1. Each cuckoo lays one egg in each iteration, and the host nest is randomly selected.
2. The nests with better quality are transferred to the next iteration.
3. There is the probability of Pa (between 0 and 1) to find the egg laid by the cuckoo.

After that, the cuckoo lays an egg in a host's nest, and other birds may find the cuckoo's egg and discard the egg or leave the nest. This process is down by the probability of Pa. Also, in CS, cuckoos search according to levy flight distribution to find host nests. For more information about CS, please refer to the study of [50].

3.7. Bat algorithm (BA)

The echolocation ability of microbat inspires the BA [51]. This algorithm was used in other fields, such as drought forecasting [52]. In nature, microbats emit loud sounds to the surrounding environment and receive their echo. Then, according to the time interval between the emitted sound and received echo, microbats detect the prey and obstacles. The BA algorithm is designed based on the following rules:

1. All bats use echolocation ability to find prey and the obstacle.
2. All bats randomly fly in the problem's search space by the velocity of V_i^t, the minimum frequency of f_{min}, and loudness of A in the position of X_i^t.

3. The loudness is varied between A_{min} and A_{max}. For more details about BA, please refer to [53].

3.8. Shark smell optimization (SSO)

SSO [54] is inspired by the hunting ability of sharks to move to an odor source based on their sense of smell.

This algorithm is designed based on the following idea:

1. The prey is injured fish, and blood is regularly released into seawater. Also, the effect of seawater flow in distorting the odor particles is not considered.
2. Only one blood source (injured fish or prey) exists.

In SSO, each shark has one velocity vector, one position vector, and one objective function, in which the objective function shows the odor intensity. In this algorithm, first, the velocity of each shark is updated based on the gradient of the objective function. Then, the position of the sharks is updated according to the current velocity. Moreover, the SSO uses rotation movement to achieve more accuracy. The position of sharks in this strategy is updated as follows:

$$Z_i^{t+1,m} = X_i^{t+1} + R * X_i^{t+1} \tag{7}$$

In which, $Z_i^{t+1,m}$ is the updated position of the shark by rotation strategy, X_i^{t+1} is the current position of the shark, R is a random number between −1 and 1. For more information about SSO, please see [43].

3.9. Whale optimization algorithm (WOA)

The WOA inspires of hunting behaviors of humpback whales. In this behavior, humpback whales establish unique babbles as a circle or spiral path around school fish to hunt them. This algorithm constructs from encircling prey and bubble-net attack sections. The encircling of prey is done by moving whales toward prey as follows:

$$D = \left| C * X_{best}(t) - X(t) \right| \tag{8}$$

$$X(t+1) = X_{best}(t) - A * D \tag{9}$$

In which, X_{best} is the best position of all whales in iteration, t, X position of the whale, A, and D are coefficient vectors calculated by relations 8 and 9. Coefficient vectors are calculated as follows:

$$A = 2 \times a \times r_1 - a \tag{10}$$

$$C = 2 \times r_2 \tag{11}$$

In which, r_1 and r_2 are random vectors between 0 and 1, and a is linearly reduced from 2 to 0 by increasing iteration.

Also, bubble-net attacking is down as follows:

$$X(t+1) = D^{'} * e^{bl} * \cos(2\pi l) + X_{best}(t) \tag{12}$$

In which, D' is Euclidean distance between X_{best} and X, b is a parameter that relates to the shape of the spiral, l is a random number between −1 and 1 [20].

3.10. Harris hawks optimization (HHO)

The HHO [23] is another optimization algorithm inspired by the cooperative strategy of Harris hawk's in hunting prey. HHO was applied in other works, such as groundwater level predicting [55]. In HHO, hawks cooperatively besiege prey from different directions. In the hunting strategy of Harris, hawks are seen in different patterns based on the escaping methods of prey [56]. HHO simulates this strategy in four phases: soft besiege, hard besiege, soft besiege with progressive rapid dives, and hard besiege with advanced rapid dives. In HHO, these four phases are simulated according to two important parameters. These critical parameters are escaping energy and one random number (q). The escaping energy in HHO is calculated as follows:

$$E = 2 * E_0 * \left(1 - \frac{t}{MaxIt}\right) \tag{13}$$

In which, E is current escaping energy, E_0 is initial escaping energy, t is the current number of iterations, $MaxIt$ is the maximum number of iterations. When c and $|E|$ are both equal to or greater than 0.5, the soft besiege phase is executed. If $q \geq 0.5$ and $|E| \leq 0.5$, the besiege phase is done. If $q < 0.5$, and $|E| \geq 0.5$, the hard besiege with progressive rapid dives step is done. When q is smaller than 0.5 and the absolute value of E is less than 0.5, the approach of hard besiege with progressive rapid dives is carried out. All phases have a unique formula shown in [33].

3.11. The hybrid of WOA and CS (WOA_CS)

WOA and CS are well-known swarm-based algorithms which have unique abilities. WOA is good in local search, while CS has the ability for global search. Therefore, a combination of them can create one optimization algorithm with a good balance between local and global search. The central concept of WOA_CS is based on the communication approach between WOA and CS. In this approach, the worst solutions of each algorithm are replaced with the best solutions of another algorithm. In the communication approach, the initial population is divided into two subgroups that search independently in the problem's search space and then share information. Afterward, each subgroup's worst and best solutions are introduced to other subgroups [43]. In this method, the weaknesses of each algorithm are covered by the other algorithm. The pseudo-code of WOA_CS is as follows (Algorithm1):

3.12. Evaluation criteria

In the present study, different evaluation criteria include sum squared deviation (SSQ), sum absolute deviation (SAD), the error between calculated and observed peak outflow (EQp), the error between the time of computed and observed peak outflow (ETp), mean absolute relative error (MARE), variance index (VarexQ), agreement index (d) are used for evaluating the accuracy of MOAs. The SSQ, SAD, EQp, ETp, MARE, VarexQ, and *d* are defined as follows:

1: Define search agent number (Searchagent_n), number of nests (n), P_a, MaxIt, 2: Swap number (Ri)
3: Generate the initial population for WOA
4: Calculate the objective function (SSQ) for each whale
5: Generate the initial population for CS
6: Calculate the objective function (SSQ) for each nest
7: Ri=1: R: MaxIt
8: For it=1:MaxIt
9: Run WOA
Sort solution: evaluations of WOA based on the objective function
11: Run CS
12: Sort solutions of CS based on the objective function
13: If it==Ri then
14: Replace k number of best solutions of WOA with k number of worst solutions of CS
15: Replace k number of best solutions of CS with k number of the worst solutions of WOA
16: End
17: Update the best solution of two algorithms
18: End
19: Return the best solution (bet Muskingam parameters with minimum SSQ)

Algorithm 1. The pseudo-code of WOA_CS.

$$SSQ = \sum_{t=1}^{n} \left(Q^{t}_{Observed} - Q^{t}_{Routed} \right)^2 \tag{14}$$

$$SAD = \sum_{t=1}^{n} \left| Q^{t}_{Observed} - Q^{t}_{Routed} \right| \tag{15}$$

$$EQp = \frac{\left| Q^{peak}_{Observed} - Q^{peak}_{Routed} \right|}{Q^{peak}_{Observed}} \tag{16}$$

$$ETp = \left| T^{peak}_{Observed} - T^{peak}_{Routed} \right| \tag{17}$$

$$MARE = \frac{\left(Q^{t}_{Observed} - Q^{t}_{Routed} \right)}{N * Q^{t}_{Observed}} \tag{18}$$

$$VarexQ = \left(1 - \frac{\sum_{t=1}^{N} \left(Q^{t}_{Observed} - Q^{t}_{Routed} \right)^2}{\sum_{t=1}^{N} \left(Q^{t}_{Observed} - Q^{mean}_{Observed} \right)^2} \right) * 100 \tag{19}$$

$$d = 1 - \frac{\sum_{t=1}^{N} \left(Q^{t}_{Observed} - Q^{t}_{Routed} \right)^2}{\sum_{t=1}^{N} \left| Q^{t}_{Routed} - Q^{mean}_{observed} \right|^2 + \sum_{t=1}^{N} \left| Q^{t}_{Observed} - Q^{mean}_{Observed} \right|^2} \tag{20}$$

In which, $Q_{Observed}^{t}$ is observed outflow, Q_{Routed}^{t} is routed outflow, $Q_{Observed}^{mean}$ is the mean of the observed outflow, $Q_{Observed}^{peak}$ is the peak of observed outflow, Q_{Routed}^{peak} is the peak of routed outflow, $T_{Observed}^{peak}$ is the time of observed peak outflow, T_{Routed}^{peak} is the time of routed peak outflow, and N is the number of data.

3.13. Multi criteria decision-making (MCDM)

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [57] is one of the MCDM methods that select the best alternative based on choosing what is closest and most far from the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS), respectively [58]. This method has been used in the present study because it is more straightforward than other MCDM methods. [59]. TOPSIS chooses solutions from a set of alternatives. Specifically, the selected alternative has the smallest distance to the positive ideal solution A^{+} (PIS) and the most significant distance to the negative ideal solution A^{-} (NIS). TOPSIS is suggested for order preservation for ranking the alternatives under natural experts' errors made during expert estimation usability for many of the alternatives [60].

The TOPSIS method can be summarized as follows:

1. Create a decision matrix (D), based on *m* alternative and *n* criteria as follows:

$$D=\begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \dots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \tag{21}$$

In which, d_{ij} is element of decision matrix in i^{th} row and j^{th} column.

2. Normalize the decision matrix as follows:

$$r_{ij}=\frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}}} \tag{22}$$

Here, r_{ij} is a normalized decision matrix.

3. Calculate the weighted normalized decision matrix by defining the weight vector and multiplying the normalized decision matrix:

$$V_{m*n}=\left(W_j * r_{ij}\right)_{m*n} \tag{23}$$

In which, V_{m*n} is a weighted normalized decision matrix, and W_j is a weight of j^{th} criterion.

4. Estimate the distance of the i^{th} alternative from the A^{+} and A^{-} as follows:

$$\begin{cases} A^{+}=\left[a_1^{+}, a_2^{+}, \dots, a_n^{+}\right]=\max\left\{v_{ij} \mid i=1,2,\dots,m\right\} \\ A^{-}=\left[a_1^{-}, a_2^{-}, \dots, a_n^{-}\right]=\min\left\{v_{ij} \mid i=1,2,\dots,m\right\} \end{cases} \tag{24}$$

5. Estimate the Euclidean distance for each solution from the positive ideal (S^+) and negative ideal (S^-) as follows:

$$\begin{cases} S^+ = \sqrt{\left(v_{ij} - a_j^+\right)^2}, i = 1,2,...,m \\ S^- = \sqrt{\left(v_{ij} - a_j^-\right)^2}, i = 1,2,...,m \end{cases} \quad (25)$$

Estimate the relative closeness or score of each alternative as follows:

$$Score_i^+ = \frac{S_i^-}{S_i^- + S_i^+}, i = 1,2,...,m \quad (26)$$

In which, $Score_i^+$ is the score of the ith alternative. The alternative with more scores is the better solution. In this study, alternatives are MOAs and SSQ, SAD, EQp, ETp, MARE, VarexQ, and d are evaluation criteria.

3.14. Presented technique for discharge routing

In the present study, nine MOAs, GA, PSO, BA, CS, FFA, SSO, WOA, HHO, and WOA_CS, optimize one of the Muskingum's powerful methods to simulate the discharge in three reaches. The optimization algorithms used in this study are well-known MOAs used in many previously conducted studies. Each of these algorithms has unique operators and a specific structure for optimizing problems. The GA is the evolutionary algorithm, PSO, FFA, CS, BA, SSO, WOA, and HHO are swarm-based algorithms, and WOA_CS is the hybrid algorithm. GA works based on the natural selection theory [61]. The PSO developed based on the swarm movement of particles, birds or school fish [62]. The BA was inspired by the echolocation ability of bats [51]. CS was designed based on the lifestyle of a family of cuckoos [63]. The FFA works according to the flashing behaviour of fireflies. The SSO was designed based on the hunting method of sharks to use their smell sense [54]. The WOA was inspired by the hunting behaviour of humpback whales [20]. HHO was developed based on the hunting approach of Haris hawk's [23]. The WOA_CS worked based on the parallel hybridization of WOA and CS.

The simulation process is described as follows: Determine the parameter of MOAs.

1. The NL5 parameters include K, X, C_1, C_2, α_1, α_2 and β are considered decision variables.
2. Generate the initial population for each optimization algorithm.
3. Calculate the initial storage S_0 for each search agent and each algorithm, considering the equality of inflow and outflow:

$$S_0 = K\left[X\left(C_1 I_0^{\alpha_1}\right) + \left(1 - X\right)\left(C_2 O_0^{\alpha_2}\right)\right]^{\beta} \quad (27)$$

4. Calculate the change in storage for each search agent and each algorithm on time:

$$\frac{\Delta S_t}{\Delta t} = I_t - \left\{ \left[\frac{1}{C_2 * (1-X)} \right] * \left(\frac{S_t}{K} \right)^{\frac{1}{\beta}} - \left[\frac{1}{C_2 * (1-X)} \right] * \left[X * \left(C_1 * I_t^{\alpha_1} \right) \right] \right\}^{\frac{1}{\alpha_2}} \tag{28}$$

5. Calculate the storage for each search agent and algorithm at the time t:

$$S_{t+1} = S_t + \frac{\Delta S_t}{\Delta t} * \Delta t \tag{29}$$

6. Calculate the outflow for each search agent and each algorithm at the time $t+1$:

$$O_{t+1} = \left\{ \left[\frac{1}{C_2 * (1-X)} \right] * \left(\frac{S_t}{K} \right)^{\frac{1}{\beta}} - \left[\frac{1}{C_2 * (1-X)} \right] * \left[X * \left(C_1 * I_{t-1}^{\alpha_1} \right) \right] \right\}^{\frac{1}{\alpha_2}} \tag{30}$$

7. Calculate the objective function (SSQ) for each search agent and each algorithm.
8. Update the position of search agents based on the operators of each algorithm.
9. If the termination criterion is satisfied, go to stage 11. Else, go to stage 4.
10. Calculate the evaluation criterion.
11. Select the best optimization algorithm based on the evaluation criteria and the TOPSIS method. Figure 3 shows the presented technique for discharge routing.

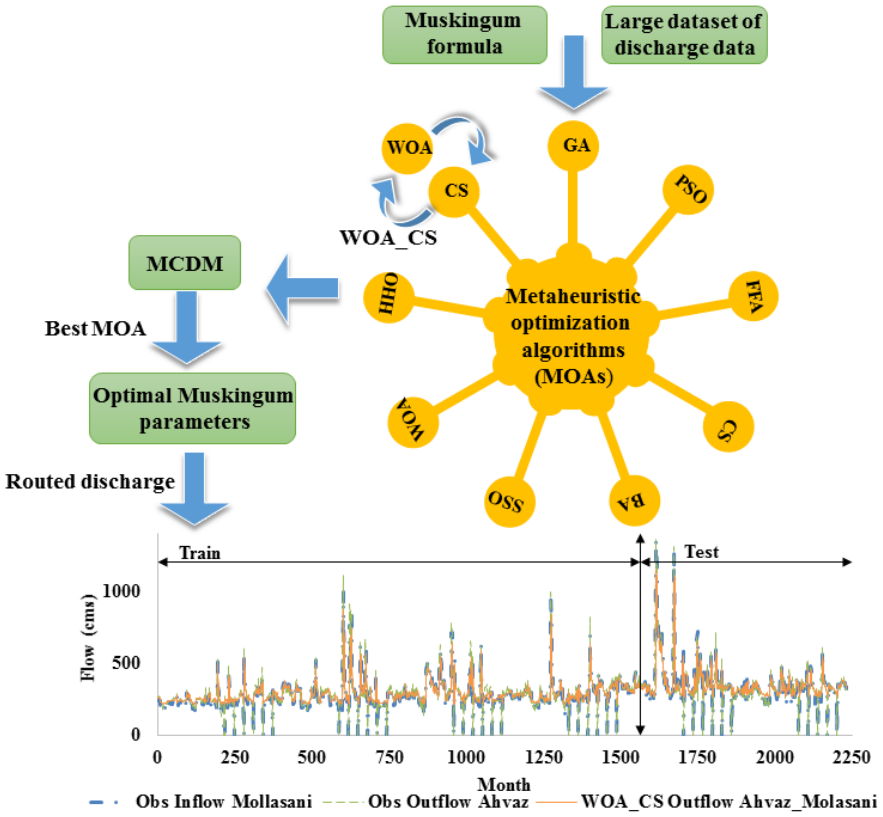


Fig. 3. Presented technique for discharge routing.

4. Results

4.1. Sensitivity analysis of the optimization algorithm

The MOAs have random parameters, which are necessary to determine. One of the best methods for choosing these parameters is sensitivity analysis. This method estimates the objective function changes by varying the optimization algorithm parameters. Then the value of the intended parameter that leads to the minimum value of the objective function (SSQ) is considered the best parameter value of the optimization algorithm. The mentioned value of SSQ is calculated based on the average of SSQ from 30 random runs of each MOA. Table 2 to Table 7 listed the best values of MOA parameters obtained by sensitivity analysis. These tables report different values for each parameter and their corresponding objective functions. Also, the best parameters of each algorithm with the minimum objective function are bold. For example, the best population size for all MOAs except for FFA and WOA_CS was 125, while the best population size for FFA and WOA_CS was 25 and 75, respectively. According to the other table results, the best P_c and P_m for GA in Ahvaz-Mollasani were equal to 0.1 and 0.6, respectively. In these tables, a dashed line in the cell corresponding to each algorithm and parameter indicates that the corresponding parameter is unrelated to that algorithm.

Table 2
Sensitivity analysis of GA, PSO, FFA, and CS for Ahvaz-Mollasani.

Parameters	Value	GA	PSO	FFA	CS
PopSize	50	7670000.00	7480000.00	9620000.00	7490000.00
	70	7630000.00	7470000.00	8550000.00	7470000.00
	100	7640000.00	7460000.00	7710000.00	7470000.00
	125	7610000.00	7450000.00	7390000.00	7460000.00
Pc	0.1	7610000.00	-	-	-
	0.3	7620000.00	-	-	-
	0.6	7610000.00	-	-	-
	0.9	7610000.00	-	-	-
Pm	0.1	7620000.00	-	-	-
	0.3	7600000.00	-	-	-
	0.6	7580000.00	-	-	-
	0.9	7670000.00	-	-	-
c1=c2	1.8	-	7460000.00	-	-
	1.9	-	7450000.00	-	-
	2.0	-	7450000.00	-	-
	2.1	-	7440000.00	-	-
Wdamp	0.7	-	7460000.00	-	-
	0.8	-	7460000.00	-	-
	0.9	-	7470000.00	-	-
	1.0	-	7460000.00	-	-
α	0.1	-	-	7450000.00	-
	0.15	-	-	7440000.00	-
	0.20	-	-	7430000.00	-
	0.30	-	-	7400000.00	-
β	0.01	-	-	7640000.00	-
	0.05	-	-	7610000.00	-
	0.10	-	-	7560000.00	-
	0.20	-	-	7460000.00	-
P_a	0.1	-	-	-	7450000.00
	0.15	-	-	-	7460000.00
	0.20	-	-	-	7460000.00
	0.25	-	-	-	7460000.00

Table 3
Sensitivity analysis of GA, PSO, FFA, and CS for Harmaleh-Bamdej.

Parameters	Value	GA	PSO	FFA	CS
PopSize	50	756000.00	740000.00	2000000000.00	739000.00
	70	755000.00	739000.00	971000.00	738000.00
	100	753000.00	739000.00	751000.00	738000.00
	125	749000.00	739000.00	737000.00	738000.00
Pc	0.1	753000.00	-	-	-
	0.3	749000.00	-	-	-
	0.6	748000.00	-	-	-
	0.9	748000.00	-	-	-
Pm	0.1	750000.00	-	-	-
	0.3	747000.00	-	-	-
	0.6	744000.00	-	-	-
	0.9	743000.00	-	-	-
c1=c2	1.8	-	739000.00	-	-
	1.9	-	739000.00	-	-
	2.0	-	739000.00	-	-
	2.1	-	739000.00	-	-
Wdamp	0.7	-	739000.00	-	-
	0.8	-	739000.00	-	-
	0.9	-	739000.00	-	-
	1.0	-	739000.00	-	-
α	0.1	-	-	737000.00	-
	0.15	-	-	737000.00	-
	0.20	-	-	737000.00	-
	0.30	-	-	737000.00	-
β	0.01	-	-	750000.00	-
	0.05	-	-	746000.00	-
	0.10	-	-	742000.00	-
	0.20	-	-	737000.00	-
P_a	0.1	-	-	-	738000.00
	0.15	-	-	-	738000.00
	0.20	-	-	-	738000.00
	0.25	-	-	-	738000.00

Table 4
Sensitivity analysis of GA, PSO, FFA, and CS for Lighvan-Heravi.

Parameters	Value	GA	PSO	FFA	CS
PopSize	50	667000000.00	1330000000.00	10000000000.00	256.00
	70	264.00	1000000000.00	10000000000.00	256.00
	100	263.00	667000000.00	9000000000.00	256.00
	125	266.00	255.00	7330000000.00	256.00
Pc	0.1	265.00	-	-	-
	0.3	286.00	-	-	-
	0.6	273.00	-	-	-
	0.9	263.00	-	-	-
Pm	0.1	263.00	-	-	-
	0.3	259.00	-	-	-
	0.6	260.00	-	-	-
	0.9	259.00	-	-	-
c1=c2	1.8	-	1000000000.00	-	-
	1.9	-	255.00	-	-
	2.0	-	333000000.00	-	-
	2.1	-	667000000.00	-	-

Table 4 (continuous)
Sensitivity analysis of GA, PSO, FFA, and CS for Lighvan-Heravi.

Parameters	Value	GA	PSO	FFA	CS
Wdamp	0.7	-	1000000000.00	-	-
	0.8	-	333000000.00	-	-
	0.9	-	257.00	-	-
	1.0	-	255.00	-	-
α	0.1	-	-	9000000000.00	-
	0.15	-	-	7330000000.00	-
	0.20	-	-	7000000000.00	-
	0.30	-	-	6670000000.00	-
β	0.01	-	-	6670000000.00	-
	0.05	-	-	5000000000.00	-
	0.10	-	-	7330000000.00	-
	0.20	-	-	7330000000.00	-
P_a	0.1	-	-	-	254.00
	0.15	-	-	-	256.00
	0.20	-	-	-	256.00
	0.25	-	-	-	256.00

Table 5
Sensitivity analysis of BA, SSO, WOA, HHO, and WOA_CS for Ahvaz-Mollasani.

Parameters	Value	BA	SSO	WOA	HHO	WOA_CS
PopSize	50	9870000.00	7690000.00	7620000.00	7520000.00	7520000.00
	70	8180000.00	7660000.00	7530000.00	7530000.00	7460000.00
	100	8220000.00	7660000.00	7500000.00	7500000.00	7430000.00
	125	7940000.00	7650000.00	7500000.00	7490000.00	7420000.00
A	0.1	8240000.00	-	-	-	
	0.3	8150000.00	-	-	-	
	0.4	8220000.00	-	-	-	
	0.6	8180000.00	-	-	-	
Qmim	0.0	8060000.00	-	-	-	-
	1.0	8120000.00	-	-	-	-
	3.0	8400000.00	-	-	-	-
	4.0	8370000.00	-	-	-	-
Qmax	1	8200000.00	-	-	-	-
	2	8140000.00	-	-	-	-
	4	8330000.00	-	-	-	-
	5	8280000.00	-	-	-	-
θ	0.7	-	7660000.00	-	-	-
	0.8	-	7650000.00	-	-	-
	0.9	-	7630000.00	-	-	-
	1.0	-	7650000.00	-	-	-
Pa	0.1	-	-	-	-	7410000.00
	0.15	-	-	-	-	7400000.00
	0.20	-	-	-	-	7440000.00
	0.30	-	-	-	-	7420000.00
Ri	0.01	-	-	-	-	7410000.00
	0.05	-	-	-	-	7350000.00
	0.10	-	-	-	-	7390000.00
	0.20	-	-	-	-	7410000.00
N_Swap	0.1	-	-	-	-	7440000.00
	0.15	-	-	-	-	7400000.00
	0.20	-	-	-	-	7410000.00
	0.25	-	-	-	-	7370000.00

Table 6
Sensitivity analysis of BA, SSO, WOA, HHO, and WOA_CS for Harmaleh-Bamdej.

Parameters	Value	BA	SSO	WOA	HHO	WOA_CS
PopSize	50	1040000.00	763000.00	749000.00	748000.00	739000.00
	70	862000.00	761000.00	743000.00	746000.00	738000.00
	100	817000.00	761000.00	743000.00	741000.00	737000.00
	125	800000.00	754000.00	742000.00	740000.00	737000.00
A	0.1	825000.00	-	-	-	
	0.3	803000.00	-	-	-	
	0.4	884000.00	-	-	-	
	0.6	812000.00	-	-	-	
Qmim	0.0	807000.00	-	-	-	-
	1.0	820000.00	-	-	-	-
	3.0	838000.00	-	-	-	-
	4.0	817000.00	-	-	-	-
Qmax	1	826000.00	-	-	-	-
	2	832000.00	-	-	-	-
	4	833000.00	-	-	-	-
	5	817000.00	-	-	-	-
θ	0.7	-	754000.00	-	-	-
	0.8	-	756000.00	-	-	-
	0.9	-	755000.00	-	-	-
	1.0	-	758000.00	-	-	-
Pa	0.1	-	-	-	-	737000.00
	0.15	-	-	-	-	737000.00
	0.20	-	-	-	-	737000.00
	0.30	-	-	-	-	737000.00
Ri	0.01	-	-	-	-	739000.00
	0.05	-	-	-	-	737000.00
	0.10	-	-	-	-	737000.00
	0.20	-	-	-	-	737000.00
N_Swap	0.1	-	-	-	-	738000.00
	0.15	-	-	-	-	737000.00
	0.20	-	-	-	-	737000.00
	0.25	-	-	-	-	737000.00

Table 7
Sensitivity analysis of BA, SSO, WOA, HHO, and WOA_CS for Lighvan-Heravi.

Parameters	Value	BA	SSO	WOA	HHO	WOA_CS
PopSize	50	1670000000.00	294.00	333000000.00	333000000.00	267.00
	70	667000000.00	288.00	333000000.00	259.00	256.00
	100	333000000.00	284.00	270.00	258.00	255.00
	125	318.00	282.00	258.00	257.00	255.00
A	0.1	317.00	-	-	-	-
	0.3	451.00	-	-	-	-
	0.4	667000000.00	-	-	-	-
	0.6	333000000.00	-	-	-	-
Qmim	0.0	667000000.00	-	-	-	-
	1.0	337.00	-	-	-	-
	3.0	417.00	-	-	-	-
	4.0	336.00	-	-	-	-
Qmax	1	532.00	-	-	-	-
	2	319.00	-	-	-	-
	4	401.00	-	-	-	-
	5	339.00	-	-	-	-

Table 7 (continuous)
Sensitivity analysis of BA, SSO, WOA, HHO, and WOA_CS for Lighvan-Heravi.

Parameters	Value	BA	SSO	WOA	HHO	WOA_CS
θ	0.7	-	282.00	-	-	-
	0.8	-	283.00	-	-	-
	0.9	-	283.00	-	-	-
	1.0	-	279.00	-	-	-
Pa	0.1	-	-	-	-	255.00
	0.15	-	-	-	-	255.00
	0.20	-	-	-	-	254.00
	0.30	-	-	-	-	255.00
Ri	0.01	-	-	-	-	255.00
	0.05	-	-	-	-	255.00
	0.10	-	-	-	-	255.00
	0.20	-	-	-	-	255.00
N_Swap	0.1	-	-	-	-	255.00
	0.15	-	-	-	-	255.00
	0.20	-	-	-	-	255.00
	0.25	-	-	-	-	255.00

4.2. Results of 30 random runs of MOAs for discharge routing

The results of 30 random runs of MOAs and statistical criteria for Ahvaz-Mollasani, Harmaleh-Bamdej, and Lighvan-Heravi are presented in Table 8, Table 9, and Table 10. According to the results of mentioned Tables, the minimum SSQ for Ahvaz-Mollasani and Lighavan-Heravi reaches were for WOA_CS, while in Bamdej-Harmaleh reach, it is for FFA and WOA_CS with a slight difference. The minimum average of SSQ in all reaches was also for WOA_CS.

Table 8
Statistical criteria run of MOAs for discharge routing in Ahvaz-Mollasani over 30 random runs.

Algorithm	Mean	Max	Min	Std	CV	Run time (sec)
GA	7582243.73	7641530.3	7401508.4	48823.76	0.01	36.64
PSO	7462058.7	7496591.27	7305166.65	31597.77	0	85.23
FFA	7461242.7	7685104.83	7305122.75	94766.55	0.01	13.89
CS	7463442.87	7509080.19	7315186.62	46570.52	0.01	26.99
BA	8180967.69	14049832.1	7476748.45	1211026.73	0.15	17.55
SSO	7656993.44	7799479.44	7449225.41	61484.03	0.01	115.1
WOA	7497059.49	7606087.6	7346273.79	46892.73	0.01	44.84
HHO	7490400.36	7624217.55	7328248.59	43290.6	0.01	46.09
WOA_CS	7352808.49	7450544.36	7305126.2	61849.65	0.01	20.72

The lower values of the difference between maximum and minimum, standard deviation (Std), and coefficient of variation (CV) show the quality of the results of MOAs. Whatever the mentioned statistical criteria for one MOA are lower, the quality of its results is higher. CV is one of the best criteria for analyzing the quality of results. As seen, for the reach of Ahvaz-Mollasani, the minimum 30 random runs of CV was related to the PSO algorithm. While the CV of other MOAs was equal to 0.01. In Harmaleh-Bamdej's reach, the CV of PSO, FFA, CS, and WOA_CS was equal to 0.00, and those for GA, SSO, WOA, and HHO were equal to 0.01. The maximum values of CV (CV=0.18) in this reach were related to BA.

Table 9
Statistical criteria of MOAs for discharge routing in Harmaleh-Bamdej over 30 random runs.

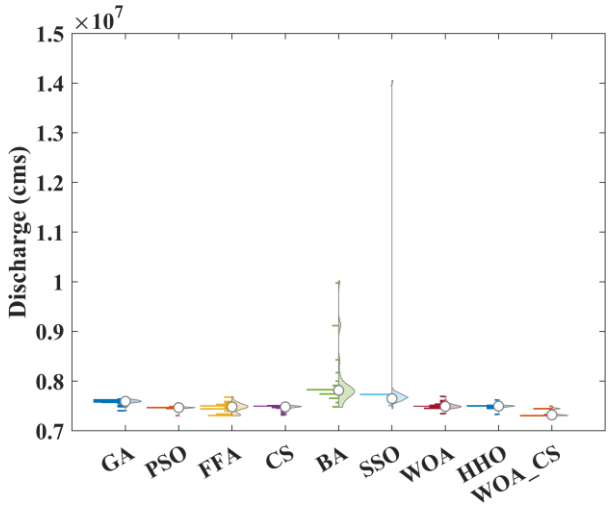
Algorithm	Mean	Max	Min	Std	CV	Run time (sec)
GA	749012.82	775758.2	736123.39	8046.12	0.01	10.67
PSO	738874.88	739514.13	735886.41	750.01	0	22.77
FFA	736875.46	739864.29	735752.67	1258.45	0	3.93
CS	738508.48	740280.52	735918.14	1008.92	0	8.96
BA	862266.55	1376172.59	741222.83	152136.45	0.18	8.29
SSO	754167.51	778137.34	738655.57	9425.79	0.01	31.61
WOA	741774.79	781567.02	735934.19	7736.52	0.01	16.35
HHO	741019.44	761434.67	736943.89	4250.31	0.01	13.13
WOA_CS	736588.9	738682.96	735761.19	1053.87	0	6.62

The results of the Lighvan-Heravi reach revealed which PSO and HHO have a minimum CV (CV=0.00), and BA has a maximum CV (CV=0.58). Moreover, in the mentioned reach, the CVs for other MOAs ranged from 0.02 to 0.09. The difference between maximum and minimum and standard deviation results confirms these results. Therefore, MOAs in Ahvaz-Mollasani optimized the Muskingum model with the most qualified, and those in Lighvan-Heravi optimized the Muskingum model with less quality. Furthermore, maximum time computing was related to the reach of Ahvaz-Mollasani, and minimum time computing was associated with the reach of Lighvan-Heravi.

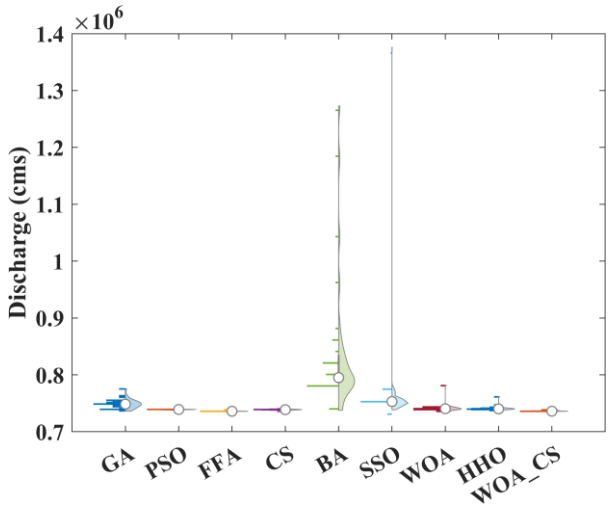
Table 10
Statistical criteria of MOAs for discharge routing in Lighvan-Heravi over 30 random runs.

Algorithm	Mean	Max	Min	Std	CV	Run time (sec)
GA	260.46	291.48	255.37	6.44	0.02	8.69
PSO	255.37	255.51	255.28	0.1	0	23.81
FFA	258.56	310.73	255.28	10.84	0.04	0.86
CS	254.08	256.11	211.48	7.91	0.03	6.26
BA	400.53	1351.95	257.38	230.85	0.58	6.11
SSO	282.02	306.19	255.71	12.54	0.04	29.56
WOA	269.82	314.09	255.3	24.43	0.09	10.56
HHO	255.87	257.64	255.34	0.52	0	8.68
WOA_CS	253.54	255.74	200.77	9.8	0.04	4.62

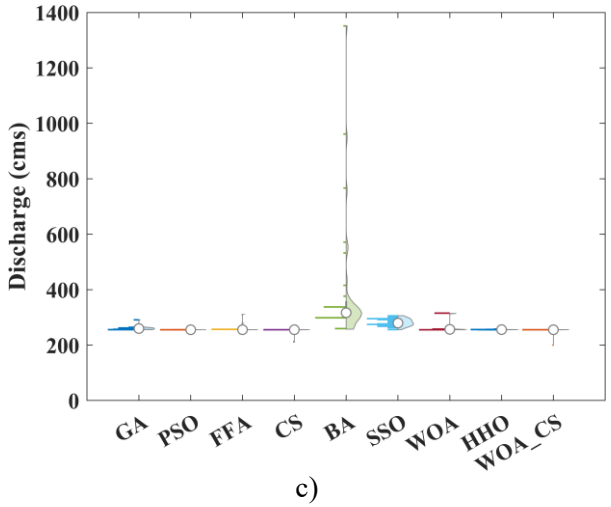
Figure 4 shows the violin plot for the objective function results over 30 runs. In this chart, the distribution, minimum, maximum and average of data are displayed. Moreover, the longer the violin diagram, the greater the uncertainty of the results. According to this diagram, PSO, CS, WOA, HHO, and WOA_CS algorithms were less uncertain than the other algorithms in the Ahvaz-Mollasani reach. Additionally, in the other two cases, the PSO, FFA, CS, WOA, HHO, and WOA_CS algorithms had less uncertainty than the other algorithms. Regarding the average objective function, WOA_CS achieved better results than other algorithms. The results of this plot are consistent with the results of Tables 8 to 10.



a)



b)

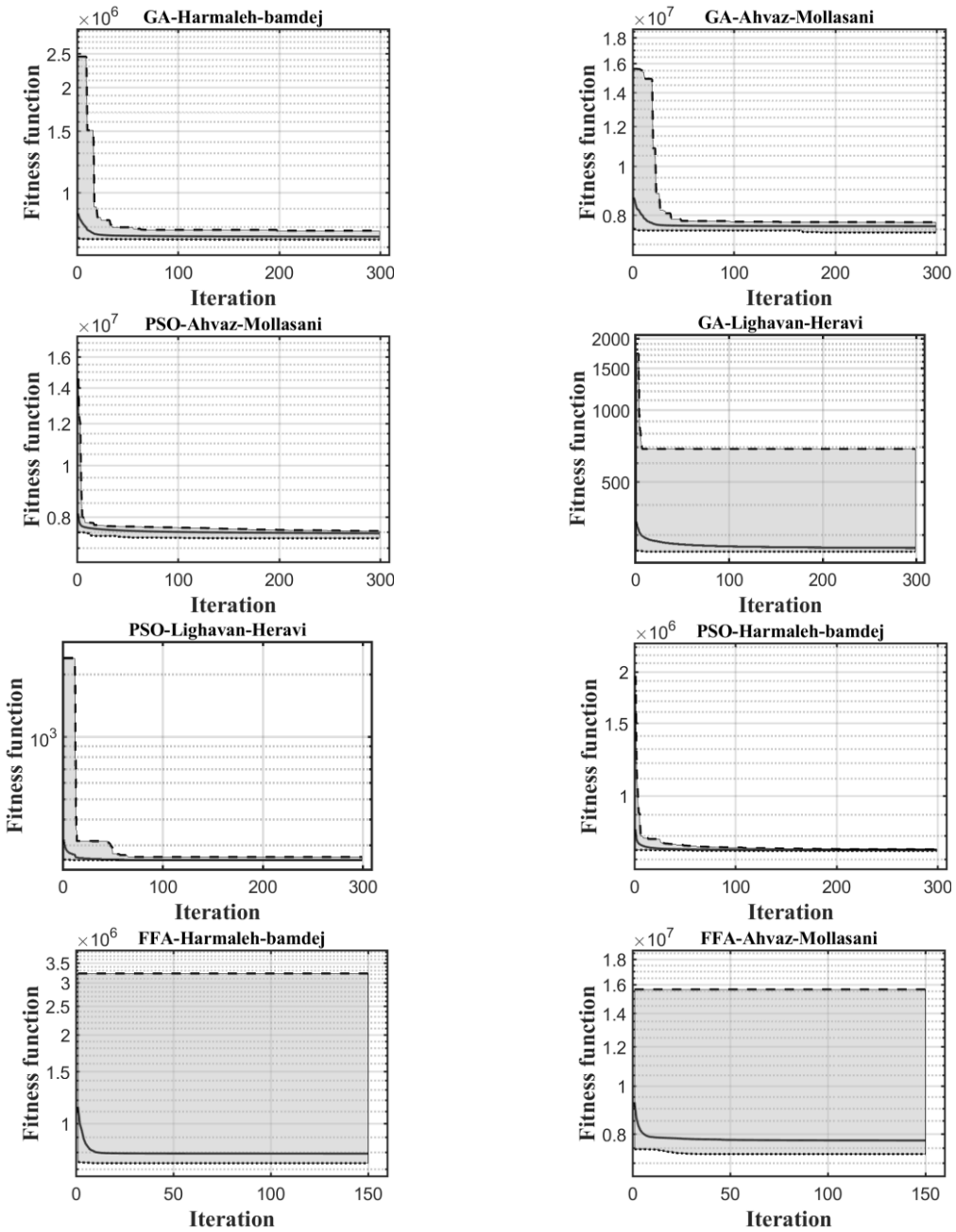


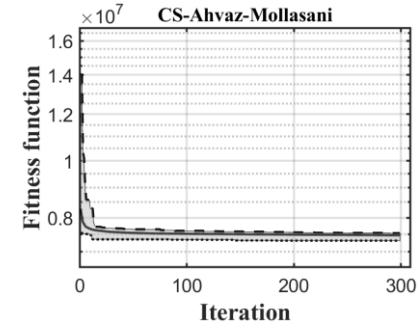
c)

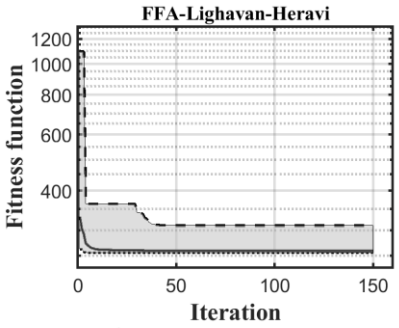
Fig. 4. violin plot of MOAs for discharge routing over 30 random runs and in a) Ahvaz-Mollasani, b) Harmaleh-Bamdej, and c) Lighvan-Heravi.

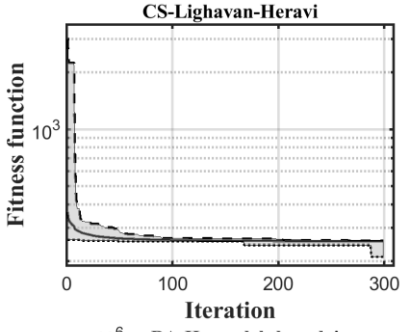
4.3. Convergence curve of MOAs in discharge routing

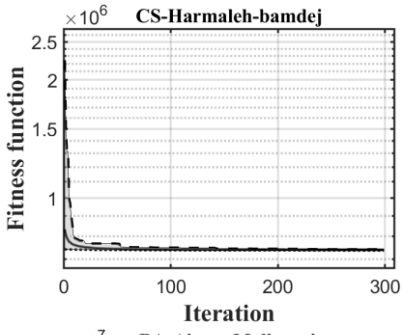
Figure 5 shows the convergence curve of MOAs for different reaches. This Figure shows the minimum, mean, and maximum of 30 random runs. The lower difference between the minimum and maximum results shows more quality of results. As seen, PSO, CS, HHO, and WOA_CS have results with more quality than other MOAs. In addition, FFA converged to the optimal solution in 150 iterations, while other algorithms converged to the optimal solution in 300 iterations.

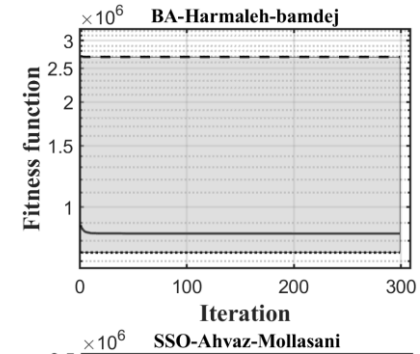


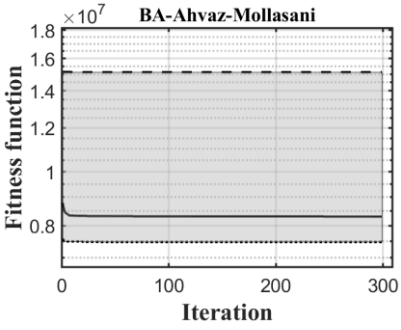

CS-Ahvaz-Mollasani
×10^7
Fitness function
Iteration

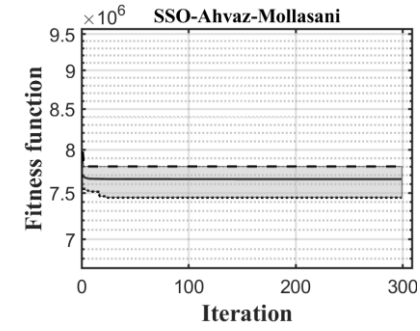

FFA-Lighavan-Heravi
Fitness function
Iteration

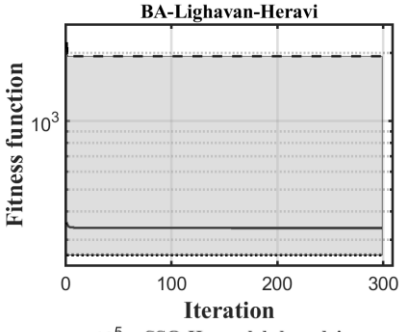

CS-Lighavan-Heravi
Fitness function
Iteration

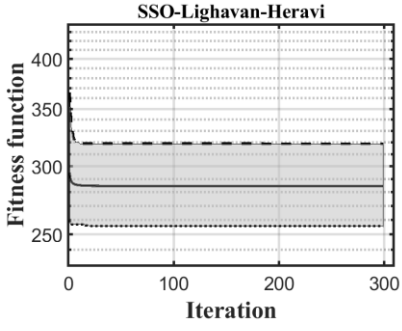

CS-Harmaleh-bamdej
×10^6
Fitness function
Iteration

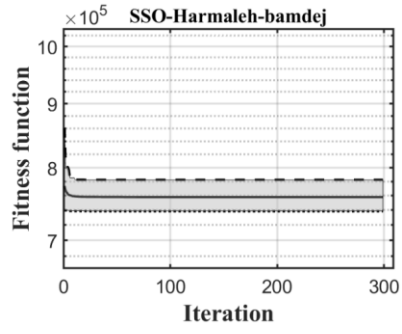

BA-Harmaleh-bamdej
×10^6
Fitness function
Iteration


BA-Ahvaz-Mollasani
×10^7
Fitness function
Iteration


SSO-Ahvaz-Mollasani
×10^6
Fitness function
Iteration


BA-Lighavan-Heravi
Fitness function
Iteration


SSO-Lighavan-Heravi
Fitness function
Iteration


SSO-Harmaleh-bamdej
×10^5
Fitness function
Iteration

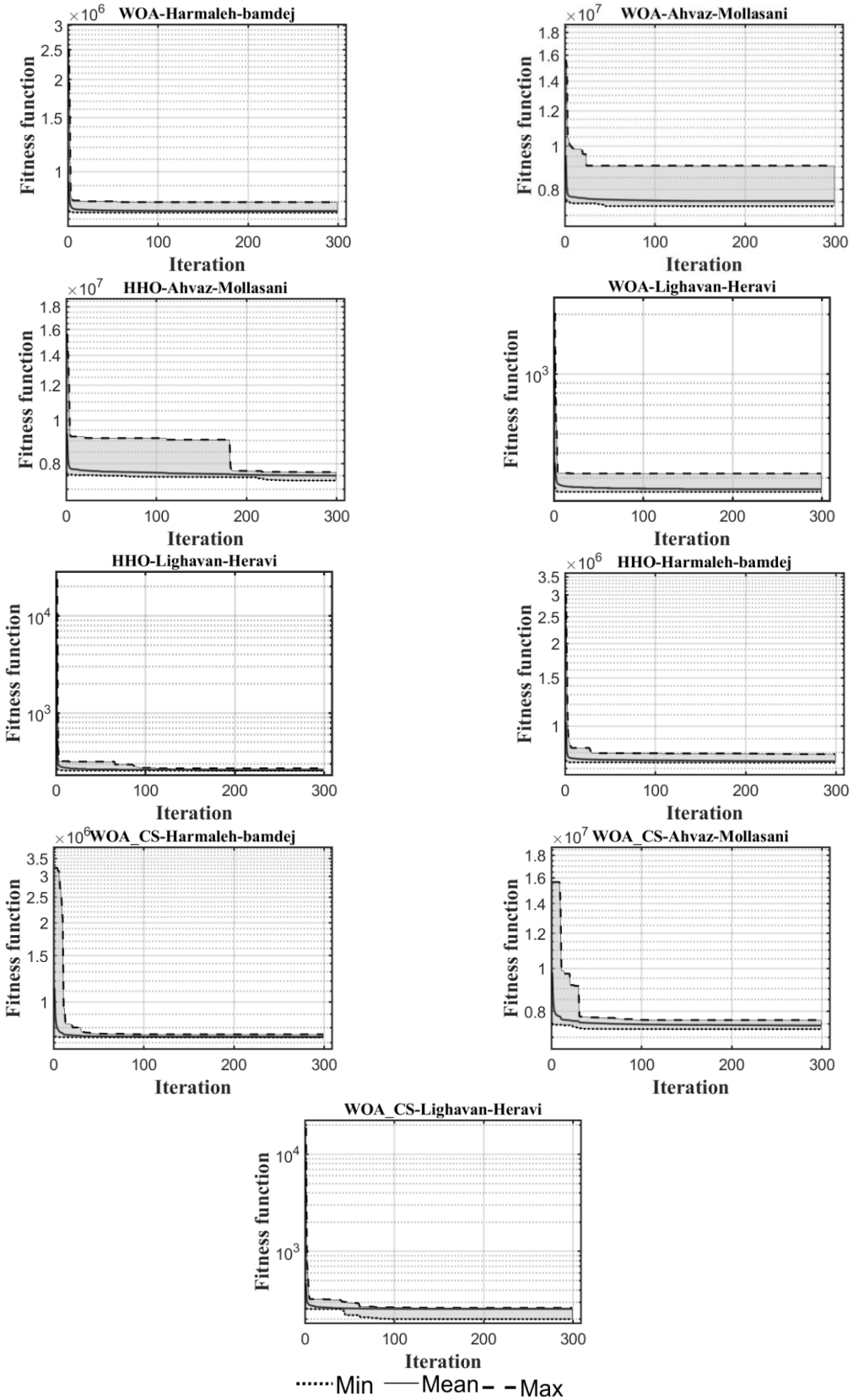


Fig. 5. Convergence curve of MOAs in different reaches.

4.4. Accuracy of MOAs in discharge routing

In this section, the results of MOAs are compared. Table 11 tabulates the calculated evaluation criteria of MOAs for the three investigated river reaches in the training period. As seen in the training period, all investigated algorithms reasonably simulate river discharge. The results of discharge routing in the testing period are presented in Table 12. In this table, the best outcome for each criterion is bold. Although the results are close to each other, each of the competing algorithms was more accurate than the others based on some evaluation criteria. In contrast, other algorithms were more accurate considering other criteria. For example, in the Lighvan-Heravi River reach, BA had better results on the Varex and d, while SSO had better results based on the SSQ, EQp, ETp, and MARE criteria. Therefore, it cannot say which algorithm is superior to other algorithms. Hence, the TOPSIS method chooses the best algorithm based on all the criteria.

Table 11
Accuracy of optimization algorithm in the training period.

Algorithms	Mollasani-Ahvaz						
	SSQ	SAD	EQ_p	ET_p	MARE	Varex	d
GA	7401508.40	53866.43	0.21	2.00	0.09	47.20	0.81
PSO	7305166.65	53711.04	0.27	2.00	0.09	47.89	0.79
FFA	7305122.75	53699.64	0.27	2.00	0.09	47.89	0.79
CS	7315186.62	53772.16	0.29	2.00	0.09	47.82	0.79
BA	7591075.36	56965.11	0.19	2.00	0.10	45.85	0.79
SSO	7449225.41	55400.05	0.25	2.00	0.09	46.86	0.80
WOA	7346273.79	53594.59	0.25	2.00	0.09	47.59	0.80
HHO	7328248.59	53702.94	0.24	2.00	0.09	47.72	0.80
WOA_CS	7305126.20	53703.91	0.27	2.00	0.09	47.89	0.79
Algorithms	Harmaleh-Bamdej						
	SSQ	SAD	EQ_p	ET_p	MARE	Varex	d
GA	736123.39	21607.70	0.12	22.00	0.19	75.53	0.93
PSO	735886.41	21600.12	0.10	22.00	0.19	75.54	0.93
FFA	735752.67	21589.72	0.09	22.00	0.19	75.54	0.93
CS	735918.14	21629.20	0.09	22.00	0.19	75.54	0.93
BA	747313.11	21743.55	0.19	22.00	0.20	75.16	0.93
SSO	738655.57	21716.26	0.11	22.00	0.19	75.44	0.93
WOA	735934.19	21620.14	0.10	22.00	0.19	75.53	0.93
HHO	736943.89	21610.83	0.14	22.00	0.19	75.50	0.93
WOA_CS	735761.19	21597.55	0.12	22.00	0.19	75.53	0.93
Algorithms	Lighvan-Heravi						
	SSQ	SAD	EQ_p	ET_p	MARE	Varex	d
GA	255.37	517.00	0.07	1.00	3.61	22.63	0.80
PSO	255.28	516.55	0.05	1.00	3.60	22.66	0.80
FFA	255.28	516.55	0.05	1.00	3.60	22.66	0.80
CS	255.67	515.32	0.13	1.00	3.60	22.54	0.80
BA	264.84	535.57	0.08	1.00	3.84	19.76	0.78
SSO	255.71	514.41	0.08	1.00	3.61	22.53	0.80
WOA	255.30	516.98	0.05	1.00	3.60	22.65	0.80
HHO	255.34	516.96	0.02	1.00	3.60	22.64	0.80
WOA_CS	256.42	520.02	0.06	1.00	3.62	22.31	0.79

Table 12
Accuracy of optimization algorithm in the testing period.

Algorithms	Mollasani-Ahvaz						
	SSQ	SAD	EQ_P	ET_P	MARE	Varex	d
GA	5750457.90	28926.76	0.14	1.00	0.10	60.51	0.87
PSO	5899562.65	29324.37	0.23	1.00	0.09	59.49	0.85
FFA	5900942.00	29321.90	0.23	1.00	0.09	59.48	0.85
CS	5977784.03	29463.27	0.25	1.00	0.09	58.95	0.84
BA	5835758.33	30315.48	0.11	1.00	0.10	59.92	0.87
SSO	5900762.44	30381.30	0.19	1.00	0.10	59.48	0.86
WOA	5813904.44	28989.04	0.19	1.00	0.09	60.07	0.86
HHO	5786612.47	28888.49	0.19	1.00	0.09	60.26	0.86
WOA_CS	5902464.18	29327.04	0.23	1.00	0.09	59.47	0.85
Algorithms	Harmaleh-Bamdej						
	SSQ	SAD	EQ_P	ET_P	MARE	Varex	d
GA	3062702.70	19129.99	0.01	2.00	0.21	74.08	0.91
PSO	3112585.15	19564.90	0.05	2.00	0.21	73.65	0.91
FFA	3116244.06	19547.68	0.05	2.00	0.21	73.62	0.91
CS	3112828.61	19463.93	0.05	2.00	0.21	73.65	0.91
BA	3040121.99	18798.16	0.09	2.00	0.19	74.27	0.92
SSO	3081733.89	19015.86	0.03	2.00	0.19	73.92	0.91
WOA	3088148.35	19190.95	0.03	2.00	0.20	73.86	0.91
HHO	3038832.86	18846.19	0.02	2.00	0.20	74.28	0.92
WOA_CS	3124220.37	19687.93	0.05	2.00	0.21	73.56	0.91
Algorithms	Lighvan-Heravi						
	SSQ	SAD	EQ_P	ET_P	MARE	Varex	d
GA	628.39	337.41	0.54	1.00	5.40	39.44	0.76
PSO	628.67	338.46	0.56	1.00	5.43	39.42	0.75
FFA	628.68	338.46	0.56	1.00	5.43	39.42	0.75
CS	614.63	332.05	0.48	1.00	5.29	40.77	0.77
BA	648.77	349.79	0.53	1.00	5.76	37.48	0.74
SSO	622.01	337.71	0.52	1.00	5.26	40.06	0.76
WOA	630.63	337.89	0.55	1.00	5.45	39.23	0.75
HHO	633.40	340.35	0.58	1.00	5.47	38.96	0.75
WOA_CS	614.57	336.31	0.52	1.00	5.52	40.77	0.77

In the following, Taylor's diagram (Figure 6) is employed to evaluate MOAs based on three criteria: standard deviation, root mean square of deviations and correlation coefficient. As can be seen, all the MOAs have a reasonable performance in terms of accuracy. Also, the results of the MOAs were similar to each other. By comparing the Taylor diagrams of the three reaches, the results show that the modeling was done more accurately in the Harmaleh-Bamdej reach and less accurately in the Lighvan-Heravi reach.

Figure 7 shows the relative results of the Nemenyi test for all MOAs based on the absolute difference between the observed and the routed outflow. Methods with higher rankings are to the right and those with lower rankings are to the left. MOAs within a horizontal line of critical distance or shorter are statistically identical. It was noted that on the first and second reach, HHO, and third reach, CS outperforms other MOAs.

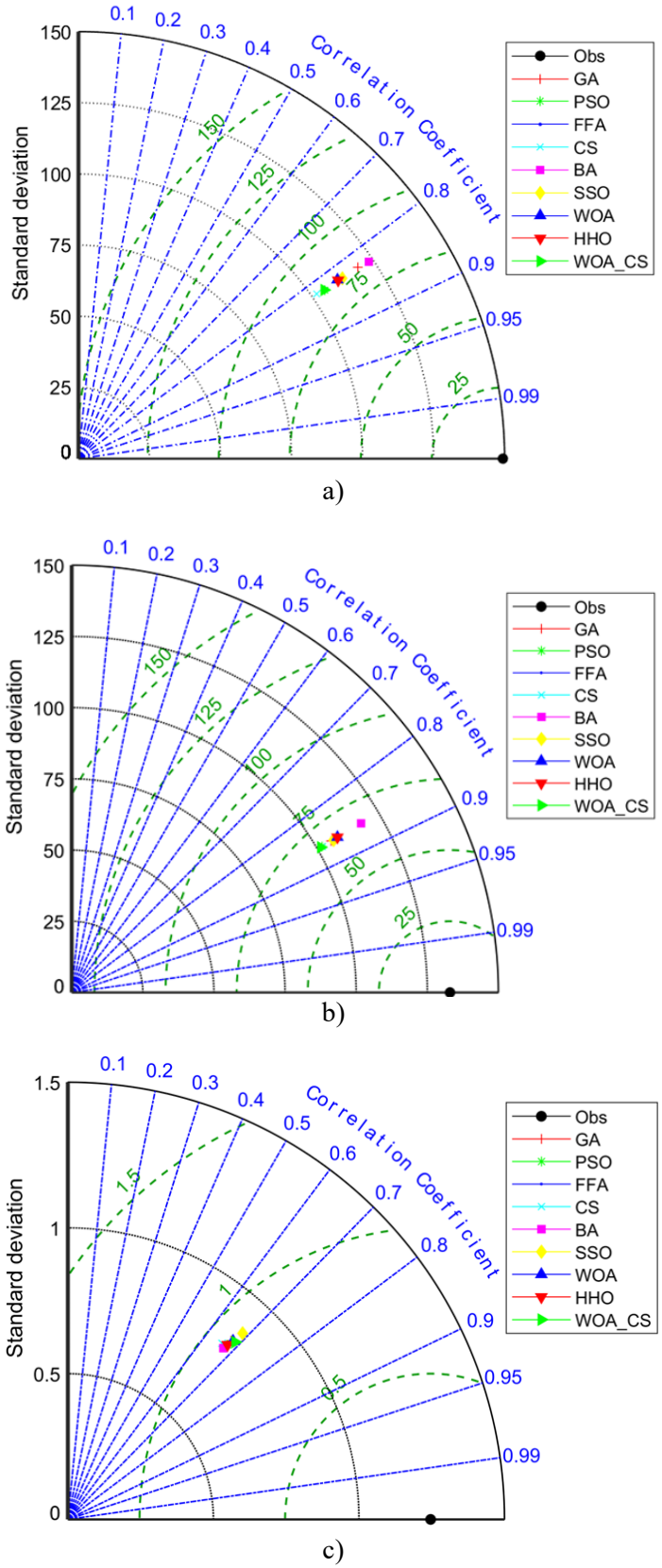


Fig. 6. Taylor diagram of MOAs in a) Ahvaz-Mollasani, b) Harmaleh-Bamdej, and c) Lighvan-Heravi.

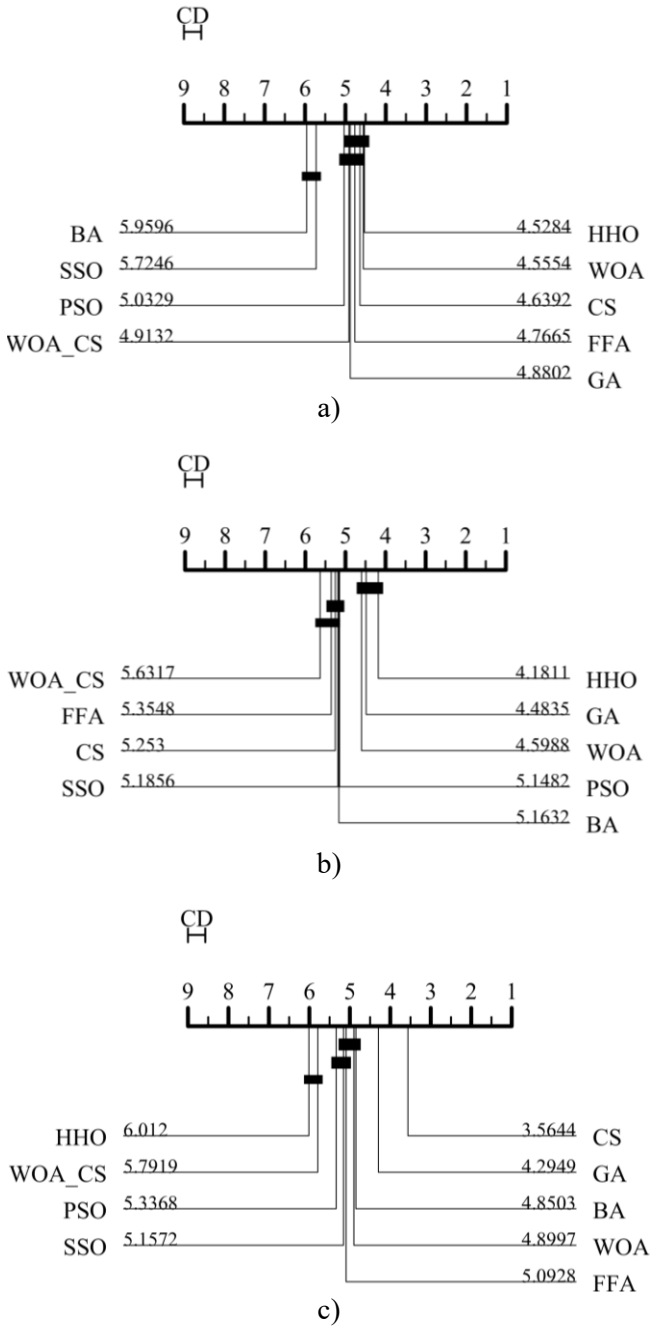


Fig. 7. Graphical representation of the Nemenyi test of MOAs in a) Ahvaz-Mollasani, b) Harmaleh-Bamdej, and c) Lighvan-Heravi.

4.5. MCDA results in discharge routing

Because choosing the best MOAS according to different criteria such as average results and best results leads to choosing different MOAs. The TOPSIS method is used for the selection of the best algorithm. In this method, various criteria such as error evaluation metrics and Nemenyi test ranks for the best results in 30 runs, the average value of the objective function in 30 runs, the value of the coefficient of variation in 30 runs and execution time have been employed to select

the best algorithm. Table 13 presents the scores and rankings of MOAs in the discharge routing obtained by TOPSIS. According to the author's experience, the weights of these criteria were equal to 0.0313 for error evaluation metrics and Nemenyi test, and 0.25 for the average value of the objective function in 30 runs, the value of the coefficient of variation in 30 runs, and execution time. WOA_CS (rank=1), FFA (rank=1), and WOA_CS (rank=1) have more scores in Mollasani-Ahvaz, Harmaleh-Bamdej, and Lighvan-Heravi River reaches, respectively.

Table 13
The optimization algorithm scores and ranks.

Algorithms	Mollasani-Ahvaz	Harmaleh-Bamdej	Lighvan-Heravi
GA	0.73 (Rank=6)	0.89 (Rank=6)	0.90 (Rank=4)
PSO	0.85 (Rank=3)	0.91 (Rank=5)	0.85 (Rank=5)
FFA	0.83 (Rank=4)	0.97 (Rank=1)	0.92 (Rank=3)
CS	0.62 (Rank=7)	0.83 (Rank=7)	0.68 (Rank=7)
BA	0.02 (Rank=9)	0.08 (Rank=9)	0.13 (Rank=9)
SSO	0.82 (Rank=5)	0.92 (Rank=4)	0.84 (Rank=6)
WOA	0.85 (Rank=2)	0.93 (Rank=2)	0.96 (Rank=2)
HHO	0.02 (Rank=8)	0.08 (Rank=8)	0.13 (Rank=8)
WOA_CS	0.98 (Rank=1)	0.92 (Rank=3)	0.97 (Rank=1)

The average results of Table 13 (Figure 8) demonstrates that WOA_CS (score = 0.960), WOA (score = 0.913) and FFA (score = 0.907) were ranked first, second and third.

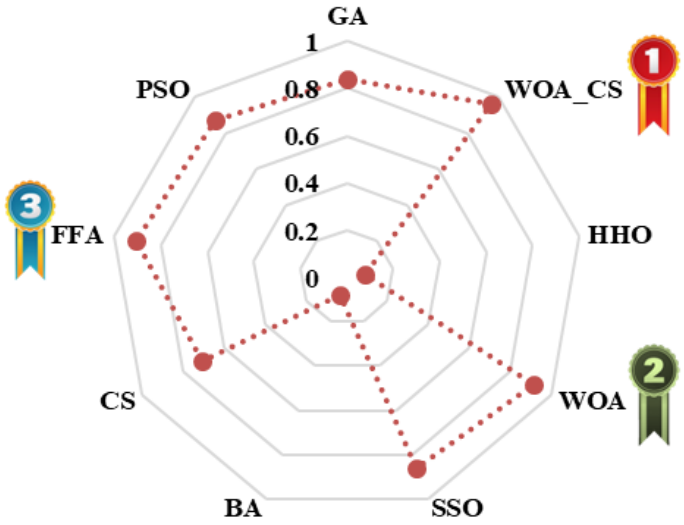


Fig.8. Average TOPSIS ranking MOAs in discharge routing.

4.6. Optimal Muskingum parameters

The optimal solutions (K, X, C_1, C_2, α_1, α_2 and β) by different MOAs are listed in Table 14. According to this table, the K, X, C_1, C_2, α_1, α_2, and β values are varied from 0.74 to 100.00, −0.80 to −0.29, 0.27 to 1, 0.00 to 0.86, 0.51 to 9.10, 0.40 to 10.00, and 0.12 to 10, respectively. Also, the range of optimal solutions was varied versus MOAs and river reaches. This issue can be found in different assumptions of algorithms and different statistical characteristics of inflow and outflow time series in river reach.

Table 14
The optimal Muskingum parameters.

	Mollasani-Ahvaz						
	K	X	C_1	C_2	α_1	α_2	β
GA	42.155	-0.781	0.903	0.002	7.884	8.777	10.000
PSO	62.268	-0.547	0.884	0.000	8.335	10.000	10.000
BA	49.655	-0.799	1.000	0.000	8.212	9.858	10.000
CS	37.044	-0.800	0.838	0.000	6.696	8.207	10.000
FFA	60.974	-0.615	0.453	0.000	7.445	8.661	10.000
SSO	12.050	-0.548	0.905	0.001	8.853	10.000	8.756
WOA	42.127	-0.800	0.323	0.000	6.316	7.364	10.000
HHO	60.974	-0.615	0.453	0.000	7.445	8.661	10.000
WOA_CS	0.749	-0.460	1.000	0.000	8.223	9.874	10.000
	Harmaleh-Bamdej						
	K	X	C_1	C_2	α_1	α_2	β
GA	42.656	-0.543	0.964	0.075	5.656	6.063	0.223
PSO	50.119	-0.800	0.938	0.018	8.021	8.791	0.150
BA	28.068	-0.297	0.543	0.003	9.099	10.000	0.151
CS	100.000	-0.531	0.678	0.006	9.038	9.927	0.123
FFA	6.516	-0.799	0.763	0.132	4.943	5.225	0.342
SSO	83.803	-0.288	0.838	0.012	7.705	8.380	8.380
WOA	8.884	-0.678	0.269	0.013	6.183	6.717	0.272
HHO	6.516	-0.799	0.763	0.132	4.943	5.225	0.342
WOA_CS	99.410	-0.457	0.997	0.008	9.092	9.995	0.118
	Lighvan-Heravi						
	K	X	C_1	C_2	α_1	α_2	β
GA	66.347	-0.571	1.000	0.658	0.950	1.079	1.481
PSO	69.355	-0.800	0.805	0.644	0.814	0.922	1.899
BA	47.327	-0.800	0.984	0.787	0.815	0.922	1.897
CS	49.186	-0.800	0.855	0.724	0.932	0.982	1.797
FFA	65.475	-0.770	0.913	0.711	0.743	0.850	2.102
SSO	40.235	-0.762	0.952	0.803	0.903	0.969	2.195
WOA	65.850	-0.649	0.953	0.667	0.874	1.002	1.584
HHO	65.475	-0.770	0.913	0.711	0.743	0.850	2.102
WOA_CS	77.557	-0.493	0.988	0.864	0.510	0.403	6.368

4.7. Outcomes of discharge routing by best algorithms

The observed inflow, observed outflow, and simulated outflow in Mollasani-Ahvaz, Harmaleh-Bamdej, and Lighvan-Heravi are demonstrated in Figures 9 to 11. The simulated outflow had good agreement with the observed outflow in all reaches. However, Mollasani-Ahvaz has the best accuracy, and Lighvan-Heravi has the weakest. As clear in Figure 10 and Figure 11, the peak of the outflow in Mollasani-Ahvaz and Lighvan-Heravi are simulated with more precision than Lighvan-Heravi, despite the excellent agreement simulated peak of outflow in all reaches.

The scatter plots of discharge routing by the best algorithms are shown in Figure 12. In this figure, the more the distribution of data around the 45-degree line, the better the performance of the algorithm. As seen, the discharge routing in Mollasani-Ahvaz and Harmaleh-Bamdej has better performance than Lighvan-Heravi. The violin plots in Figure 13 demonstrate the agreement between observed and routed discharge in Mollasani-Ahvaz and Harmaleh-Bamdej. However, the distribution of routed discharge in Lighvan-Heravi shows underestimated results. The results obtained are in agreement with the results shown in Figure 9 to Figure 11.

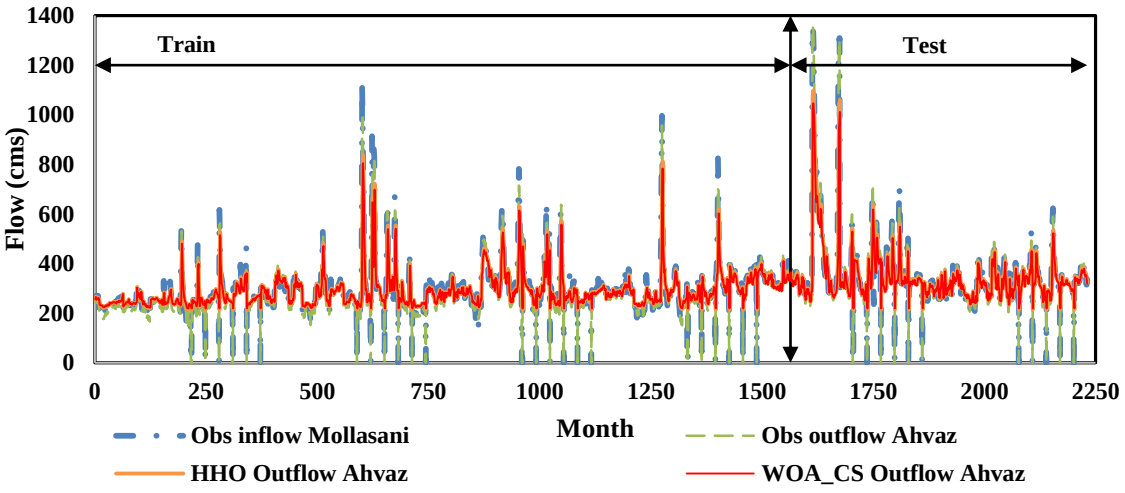


Fig. 9. The discharge routing by the best algorithm in Mollasani-Ahvaz.

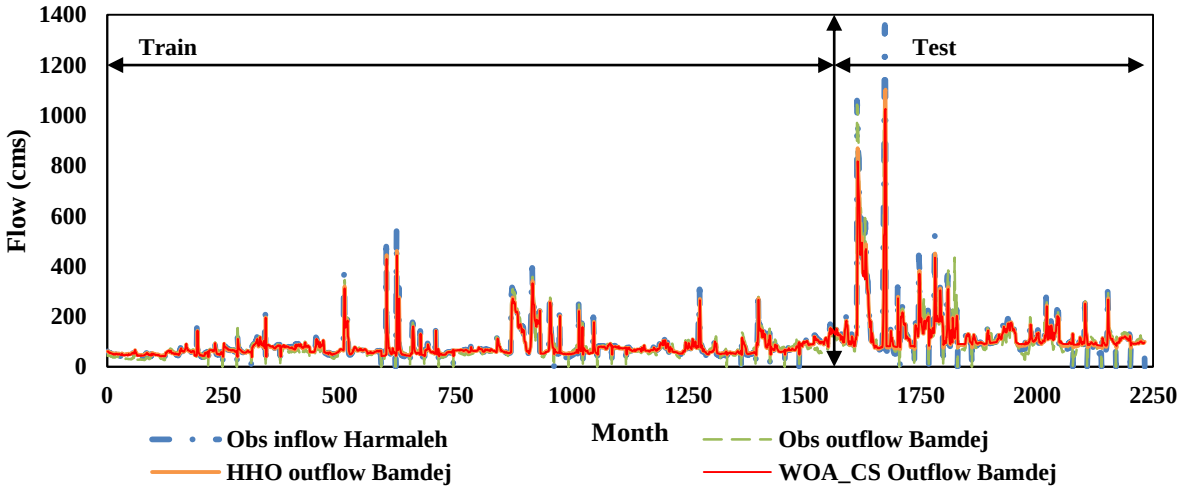


Fig 10. The discharge routing by the best algorithm in Harmaleh-Bamdej.

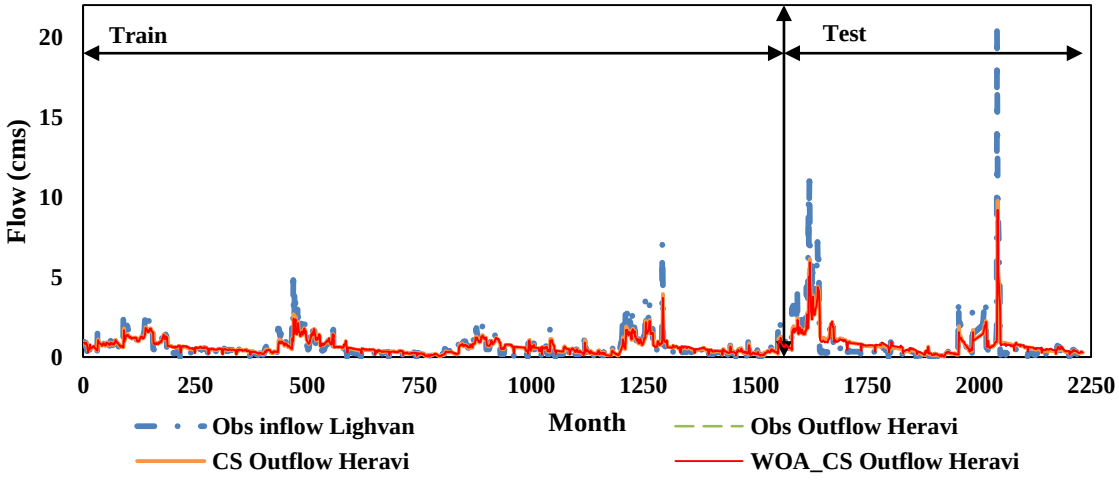
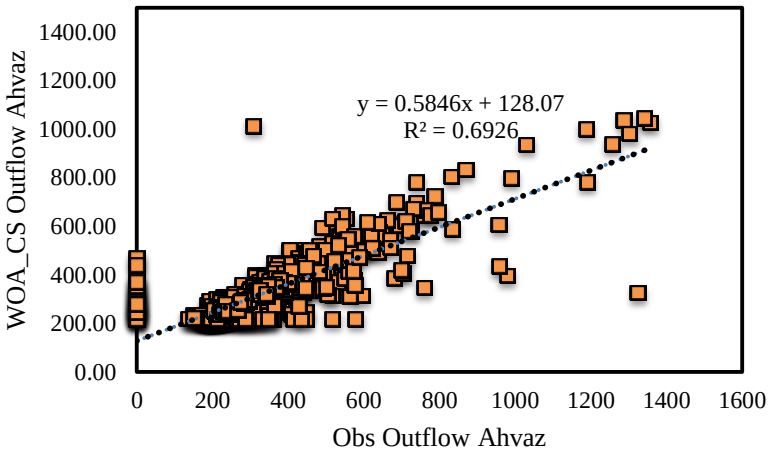
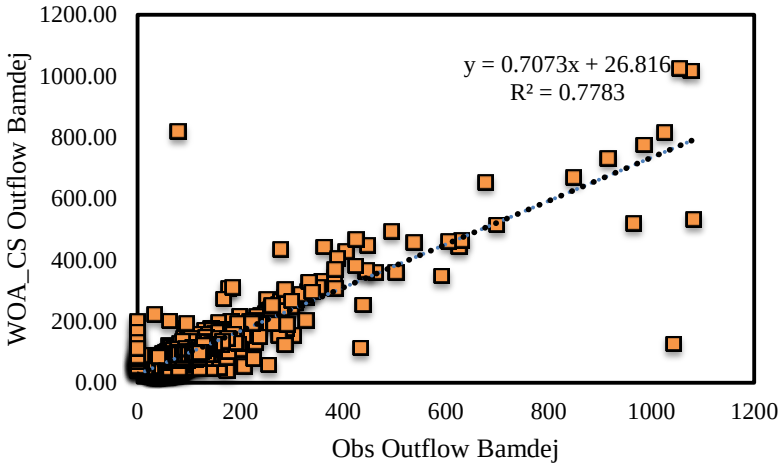


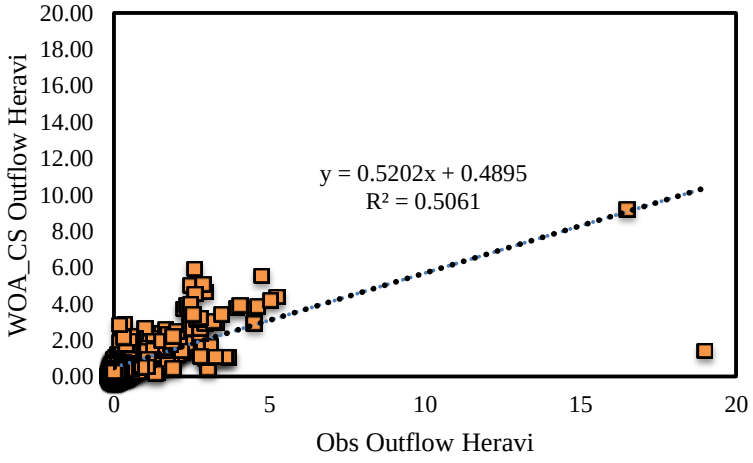
Fig. 11. The discharge routing by the best algorithm in Lighvan-Heravi.



a)



b)



c)

Fig. 12. The scatter plot of best algorithm in a) Ahvaz-Mollasani, b) Harmaleh-Bamdej, c) Lighvan-Heravi.

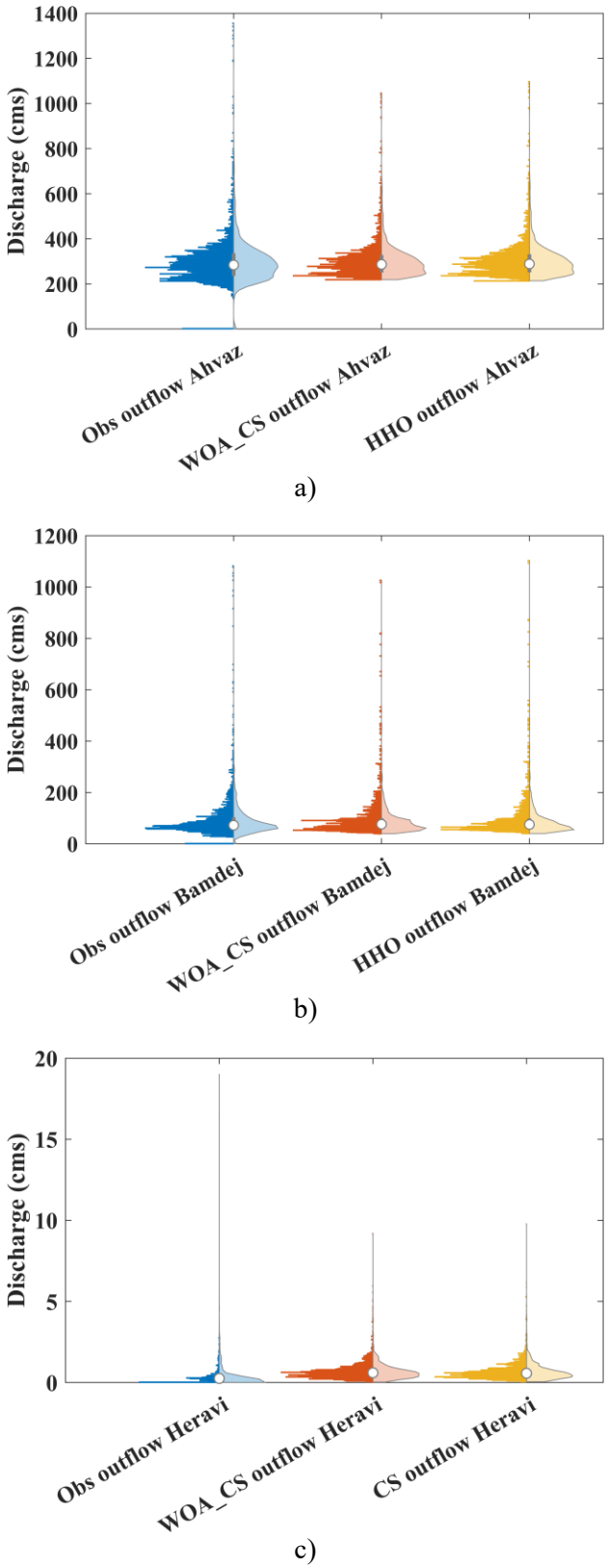


Fig. 14. The violin plot of best algorithms in a) Ahvaz-Mollasani, b) Harmaleh-Bamdej, c) Lighvan-Heravi.

5. Discussion

In this study, the results of the algorithms were different in investigated stations, and in each station, one algorithm had more accurate results than other methods. This is because the river was analyzed with different fluvial geomorphology and climate conditions, and these caused changes in the statistical characteristics of the inflow and outflow hydrographs. These differences also cause discharge routing in each river to become a specific optimization problem. According to the "No free lunch theorems for optimization" [64], each optimization algorithm performs well in a specific range of problems. For this reason, the accuracy of optimization algorithms is different in determining the optimal parameters of the Muskingum method.

Furthermore, more correlation between the inflow and outflow time series can explain the better accuracy of discharge routing in Mollasani-Ahvaz and Bamdej-Harmaleh. The method presented in the current research can be used in non-structural flood warning systems. This method can be very efficient in flood warnings when a flood occurs upstream. For this purpose, the amount of flood discharge should be measured at the upstream hydrometric station and transferred to a computer using an online system. Then, the downstream flow rate should be calculated using the current research method. Since the algorithms are pre-calibrated, this is done quickly. Finally, a flood warning is issued downstream if the calculated hydrograph peak value exceeds the allowed peak flow.

In previous studies, other methods such as SWAT [65], ANN [66], and hybrid machine learning algorithm [67] simulated river discharge with determination coefficients between 0.58-0.90 and 0.52-0.61 and 0.74-0.85, respectively. The results of the present study are close to previous studies. The method developed in this study can compete with physical and other AI algorithms. Also, the number of input features in the developed method is less than other methods such as SWAT, ANN and hybrid machine learning algorithms.

6. Conclusions

In this study, a new technique is introduced for discharge routing. The presented approach was investigated in the Mollasani-Ahvaz, Harmaleh-Bamdej River, which reaches the Karun basin, and the Lighvan-Heravi River in the Urmia basin. This study employed a range of MOAs, including GA, PSO, FFA, CS, BA, SSO, WOA, and the hybrid of WOA and CS (WOA_CS), to optimize the parameters of a highly effective Muskingum discharge routing method over an extensive dataset period. Moreover, the TOPSIS as MCDA was used for choosing the best optimization algorithm for each river reach. Based on all results of the presented technique, the following points can be concluded:

1. The accuracy of discharge routing by different MOAs was almost the same. However, each of the MOAs had good results in specific assessment criteria. Thus, the TOPSIS method was employed.
2. Results of discharge routing based on the TOPSIS showed that WOA_CS were better with considering all reach, respectively.

3. The uncertainty of WOA_CS was comparable with other MOAs. It was proved by using a coefficient of variation of 30 random runs and violin plots.
4. The execution time of WOA_CS was less than most investigated MOAs.
5. The discharge routing in all the stations was accurate, but the discharge routing in Mollasani-Ahavas had more accuracy than the other two investigated river reaches. In addition, the outflow peaks in the reaches of Ahvaz-Mollasani and Harmaleh-Bamdej were simulated with better accuracy than Lighavan-Heravi.

The presented method in this research is suitable for small and large amounts of data. But if a large dataset is used, powerful optimization algorithms are needed to determine the parameters of the Muskingum model. It should be noted that the parameter values of the optimization algorithms need sensitivity analysis before implementation. Discharge data should be divided into two periods of calibration and validation.

According to mentioned results, the introduced approach has good potential for discharge routing in other river reaches. Furthermore, this model can be improved by using other multi-criteria decision-making methods, such as integrated qualitative group decision-making.

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Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

MVA, SF, IA: Conceptualization; MVA, SF: Data curation; MVA, SF, IA: Formal analysis; SF, IA: Investigation; MVA, SF, IA: Methodology; SF, IA: Project administration; MVA, FA, IA: Resources; MVA, SF, IA: Software; SF: Supervision; MVA, SF, IA: Validation; MVA, SF, IA: Visualization; MVA, SF, IA: Roles/Writing – original draft; MVA, SF, IA: Writing – review & editing.

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